APPLICATION OF SIMULATED ANNEALING TO ECONOMIC LOAD DISPATCH PROBLEM

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CERTIFICATE

This is to certify that the work contained in thesis entitled **"Simulated Annealing applied to Economic Load Dispatch problem"** by Mr. K. Vijay has been carried out under my supervision and that has not been submitted elsewhere for a degree.

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Dedicated to

My

Parents and Sister

Acknowledgement

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Abstract

Traditionally Economic Load Dispatch problem has been solved using many conventional methods. But most of these methods assume the generator cost characteristics to be simple quadratic. And also most of them are able to tackle the constraints in a limited way. But in practice, the Economic Load Dispatch problem, demands solution when there are generators with complicated cost characteristics and various types of constraints imposed on them.

In this work, a general Simulated Annealing based Economic Load Dispatch algorithm has been presented. Methods for incorporating the transmission losses, emission dispatch constraints and prohibited zone constraints of the Economic Load Dispatch problem, into the Simulated Annealing algorithm have been worked out. Also methods for incorporating different types of cost functions like quadratic, piecewise quadratic and polynomial cost functions into the algorithm have been worked out. The effect of cooling schedule on the performance of the Simulated Annealing algorithm has been worked out in detail. The ability of the algorithm to find the global or near global optimum solution has been demonstrated by several test examples. An attempt has been made to apply Simulated Annealing Algorithm to update the weights of Hopfield Network, so as to drive the Hopfield Network to produce global optimum solution. The dispatch results obtained by applying Simulated Annealing Algorithm to various problems discussed are proven to be either more economical or equally economical in all the cases compared to the conventional methods.

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Chapter 1

Introduction

The Economic Load Dispatch problem is one of the important optimization problems in a power system, as the utilities always demand reliable supply at a cheaper cost. The economic load dispatch problem is to determine the optimal combination of power outputs for all generating units in a system which minimizes the total fuel cost of the generators while satisfying various constraints like operating limits of generators, power balance, constraints on emission levels of pollutants like SO_2, NO_x, and prohibited zone constraints on generators etc.

Many classical methods like Lagrangian method, Khun Tucker conditions, penalty factor method and iterative methods like $\lambda - \delta$ have been applied in this area. Even though these methods are good they can not handle functional inequalities. Most of the linear and nonlinear programming methods applied to this area assume a smooth quadratic cost function for generators. But it is not the case with all the generators. The fuel cost characteristic of thermal generators is usually approximated by (a) quadratic function (b) piecewise quadratic function (c) a polynomial function with order higher than two. When functions like (b) or (c) are adopted most of the conventional methods fail to work. Also in these cases, the economic load dispatch problem may have multiple local optimum solutions, one being the global optimum solution. So most of the local search techniques struggle to reach global optimum solution. Also as the complexity of the system increases the conventional methods become much more complex and occupy large computer memories as they have to store the gradients of cost functions etc. Hopfield neural networks

also have wide application in this area. But they too suffer in crossing the local optimum solution.

The simulated annealing method [1] is a powerful optimization technique and it has the ability to find global or near global optimum solutions. It can handle large combinatorial optimization problems with order higher than two. This method is similar to the local search technique, which guarantees a local optimum solution. However the simulated annealing method in addition employs a probabilistic approach in accepting the intermediate solutions in the solution process such that it can jump out of the local optimum solution. This method requires less computational effort and also occupies less computer memory, as it will not involve in the calculation of gradients.of the cost function. Also the main advantage with this method is that, it can meet the load demand and the transmission losses exactly without any mismatch. Though the computational time involved in this method is high compared to the conventional methods, because of the above-mentioned advantages, it has been applied to economic load dispatch problem.

1.1. Problem Definition

Economic load dispatch problem is one of the combinatorial optimization problems in which the objective function that has to be minimized will be nonlinear in nature and the constraints that are imposed on the system are both equality and inequality type.

This thesis explores the possibility of application of simulated annealing technique to economic load dispatch problems which involve different types of cost functions (a) quadratic (b) piecewise quadratic (c) cost function with order more than two and several constraints like power balance constraint, emission constraints on SO_2, NO_x pollutants, restricted zone constraints etc.

An attempt has been made to apply simulated annealing to update the weights of Hopfield neural network so as to make it jump out of the local minimum and produce near global optimum solution.

1.2. Past Developments and Literature Survey

The simulated annealing technique has been applied to optimization problems in power systems like unit commitment problem [2], maintenance scheduling [3], economic load dispatch [4] etc.

Work has been done on economic load dispatch with piecewise quadratic cost functions [5-6], with prohibited zones on generator operations [7-8], with emission dispatch constraints [9] etc using different optimization techniques. In the present work simulated annealing has been applied to these problems.

1.3. Organization of the thesis

- A detailed discussion about economic load dispatch problem has been presented in chapter2
- Simulated annealing algorithm and its application to economic load dispatch problem has been presented in chapter3.
- The application of simulated annealing to update the weights of Hopfield neural networks so as to move it to produce a global optimum solution has been presented in chapter4.
- In chapter5, various results have been compared and the conclusions were drawn.

Chapter 2

Economic Load Dispatch Problem

2.1 Introduction

Since every utility demands power of high quality at as much cheaper cost as possible, there has been a growing interest in the area of economic load dispatch. But in the real life economizing the cost of generation is not so easy, as we have to take care of various constraints that are imposed on the generators. In an interconnected system of generators there will be different types of units like base load units, intermediate units, peaking units, reserve units etc. which will have their own constraints in their operation. So maintaining a proper generation mix while keeping the cost of generation and reliability of the supply makes economic load dispatcher problems more complicated.

Economic load dispatch is actually a part of economic power dispatch or flow problem, which involves multiple objectives like

- Minimization of total fuel cost.
- Minimization of total loss (or) improving system voltage profile.
- Minimization of emission level.
- Minimization of control action.

So the complete optimal power flow problem determines optimal settings of both real and reactive powers.

In this present work only real power optimization has been taken to a detailed extent.

2.2 Mathematical Formulation

A general economic load dispatch problem can be formulated as,

$$\text{Min } F = \sum_{i=1}^{n} f_i(p_i) \tag{2.1}$$

Where n = number of generators

p_i = power output of i^{th} generators

subjected to

i) equality constraints:

$$h_i\,(p_1,p_2,\ldots\ldots\ldots\ldots\ldots\ldots,p_n)=0 \quad \forall i \tag{2.2}$$

ii) inequality constraints

a) Parametric inequalities (or) operating constraints

$$p_i(\min) \le p_i \le p_i(\max) \tag{2.3}$$

$$i = 1,2,\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots n$$

b) Functional inequalities

$$g_i\,(\min) \le g_i(p_1,p_2,\ldots\ldots\ldots\ldots\ldots\ldots,p_n) \le g_i(\max) \quad \forall i \tag{2.4}$$

2.2.1 Description about the Cost Function:

Different types of generators will exhibit different cost function characteristics. Most of the generators generally assume a quadratic cost function in which case the cost function in (2.1) becomes

$$\text{Min } F = \sum_{i=1}^{n} (a_i + b_i p_i + c_i p_i^2) \tag{2.5}$$

Where a_i, b_i, c_i, i=1,2,……………………n are the cost coefficients

Some generators may also have polynomial cost characteristics for their operation. Following equation represents the third order cost function

$$\text{Min } F = \sum_{i=1}^{n} (a_i + b_i p_i + c_i p_i^2 + d_i p_i^3) \tag{2.6}$$

Where a_i, b_i, c_i, d_i are cost function coefficients.

Generators which use multiple fuels for their operation will exhibit a piecewise quadratic cost function, as follows: ~~in which case the cost function becomes,~~

$$\text{Min } F = \sum_{i=1}^{n} f_i(p_i)$$

$$\text{Where,} \quad f_i(p_i) = \begin{cases} a_{i1} + b_{i1}p_i + c_{i1}p_i^2, & p_{i1}(\min) \le p_i \le p_{i1}(\max) \\ a_{i2} + b_{i2}p_i + c_{i2}p_i^2, & p_{i2}(\min) \le p_i \le p_{i2}(\max) \\ & \vdots \\ a_{ij} + b_{ij}p_i + c_{ij}p_i^2, & p_{ij}(\min) \le p_i \le p_{ij}(\max) \end{cases} \tag{2.7}$$

Where j is number of fuels available for generator i.

2.2.2 Equality Constraints

The term "reliable" always demands a zero mismatch between generation and demand. This simulates the equality constraint as:

$$(Demand + L) = \sum_{i=1}^{n} p_i \tag{2.8}$$

where L is losses in the system.

Losses can be represented by B-loss formula in the following way

$$L = \sum_{j=1}^{n}\sum_{k=1}^{n} p_j B_{jk} p_k + \sum_{i=1}^{n} B_i p_i + B_{00} \tag{2.9}$$

where B_{jk}, B_i, B_{00} are called B-loss coefficients.

An approximated version of this being

$$L = \sum_{j=1}^{n}\sum_{k=1}^{n} p_j B_{jk} p_k \tag{2.10}$$

2.2.3 Inequality constraints

a. Parametric inequalities:

Generators should always be maintained within their specified limits. Some generators may have restricted zones in which they can not be operated. So the parametric inequalities for generators can be defined as

$$p_i(\min) \le p_i \le p_i(\max), i = 1,2,.........n \tag{2.11}$$

and

$$p_i \notin \left(p_i^{(low)}, p_i^{(high)}\right) \qquad \forall i \tag{2.12}$$

where $\left(p_i^{(low)}, p_i^{(high)}\right)$ is the restricted zone for generator i.

b. Functional inequalities:

Many qualities like emission of pollutants, bus voltages etc generally depend on generator outputs. These qualities will also have some operating limits applied on them. Economic load dispatch should also take care of keeping such qualities in their desired level. For example, in the case of SO_2, NO_x limits, the emission constraints can be represented in terms of generator output by quadratic or higher order polynomials. The following equation gives insight into representation of limits.

$$\begin{aligned} &\sum_{i=1}^{Ng}\left(sa_i + sb_i p_i + sc_i p_i^2 + sd_i p_i^3\right) \le L_{SO_2} \\ &\sum_{i=1}^{Ng}\left(na_i + nb_i p_i + nc_i p_i^2 + nd_i p_i^3\right) \le L_{NO_x} \end{aligned} \tag{2.13}$$

where sa_i, sb_i, sc_i, sd_i, and na_i, nb_i, nc_i, nd_i, are polynomial emission coefficients of SO_2 and NO_x respectively.

2.3. Description about Various Economic Load Dispatch Problems Studied

In this section, a brief description about the various types of economic load dispatch problems that have been undertaken in the present work has been presented.

2.3.1. Economic Load Dispatch with Continuous Quadratic Cost Functions

These are most simple systems to solve. The ELD problem in this case will have the cost function becomes as shown below

$$\text{Min } F = \sum_{i=1}^{N}(a_i + b_i P_i + c_i P_i^2) \tag{2.14}$$

Subject to

Load balance constraint: $(\text{Demand} + L) = \sum_{i=1}^{n} p_i$ (2.15)

Where, transmission losses, $L = \sum_i \sum_j B_{ij} p_i p_j$ (2.16)

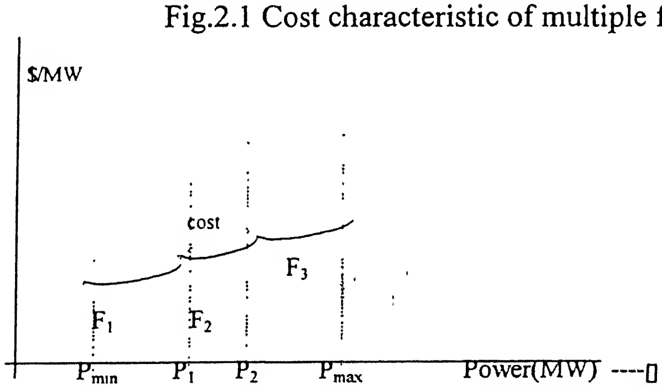
Where B_{ij} is the transmission loss coefficient.

Generation power limit constraints $p_i(\min) \leq p_i < p_i(\max)$ (2.17)

2.3.2. Economic Load Dispatch with Piecewise Quadratic Cost Functions

Traditionally in the ELD problem, the cost function for each generator will be represented by a quadratic function. However, it is more realistic to represent it for fossil fired plants as a segmented piecewise quadratic cost function, as in the case of Valve Point Loading. Some generation units, which are supplied with multiplc fuel sources like gas, oil etc., will have different cost functions when different fuels are used. In all such cases the cost function will be discontinuous in nature and can be approximated as a piecewise quadratic function, which can be shown as in Fig 2.1.

Fig.2.1 Cost characteristic of multiple fuel generator



The cost function to be optimized in this problem becomes as shown in (2.7) and subjected to constraints shown in (2.15) (2.16) and (2.17).

2.3.3. Economic Emission Dispatch

Apart from the load balance constraint, the operating limits on generators, emission of pollutants also impose constraints on the load dispatching problem. The emission of pollutants like SO_2 and NO_x are generally polynomial functions of generator loading.

Economic emission dispatch problem deals with the minimization of these pollutants. A combined Economic Load Dispatch(ELD) and Economic Emission Dispatch (EED) problem tries to minimize both cost and pollutants. Since it is not possible to minimize both of them simultaneously, generally cost is minimized subjected to the pollution constraints in a combined ELD and EED problem. So the cost function for such problems will remain same as in (2.5) (2.6) or(2.7), depending on the cost function characteristics. But the additional constraints will be imposed on the problem because of these pollutants. Since emission of these pollutants depends on the fuel used, which itself is a function of generator loadings, we can always express these emission of pollutants as a polynomial functions of generator loadings. Reference [9] discusses a way of selecting the polynomial expressions for SO_2 and NO_x in terms of generator loadings, from which the constraints (2.13) have been obtained for this problem. Apart from these constraints, the Emission Dispatch Problem will also have other constraints like load balance constraints, operating limits etc., given by (2.8), (2.9) and (2.11).

2.3.4 Economic Load Dispatch Problem with Prohibited Zones and polynomial cost function

Due to physical restrictions on power plant components, generating units may have prohibited operating zones, in their continuos operating region. When generators enter these

zones, they may result in amplifications of vibrations in shaft bearing which has to be avoided.

This type of problems will impose some more constraints on the generating units. So in this case, the ELD problem will have cost function given in (2.5) (2.6) or (2.7) depending on the cost function characteristics, and subject to constraints given in (2.15) (2.16) (2.17) and the prohibited zone constraints (2.12).

Chapter 3

Simulated Annealing And its Application to Economic Load Dispatch Problem

3.1. Introduction to Simulated Annealing

Simulated annealing which is first proposed by Kirkpatrick [1] takes the analogy between the physical annealing process of solids and the process of solving combinatorial optimization problems such as economic load dispatch problems. For this reason the algorithm became known as "Simulated Annealing". Annealing is a process whereby a solid is placed in heat bath and the temperature is continually raised until the solid has melted and the particles of the solid are physically disarranged or positioned in a random order. From this high energy level the heat bath is cooled slowly by lowering the temperature to allow the particles to align themselves in an orderly crystalline lattice structure. This final structure corresponds to a stable low energy state. The particle can reach the thermal equilibrium state at each temperature, characterized by a probability of being in a state with energy E given by the Boltzmann distribution [10],

$$\Pr\{\mathbf{E} = E\} = \frac{1}{\mathbf{Z}(T)}.\exp\left(-\frac{E}{k_B T}\right) \tag{3.1}$$

where Z(T) is a normalization factor and k_B is the Boltzmann constant. The factor $\exp\left(-\frac{E}{k_B T}\right)$ is known as Boltzmann factor. As the temperature decreases, the Boltzmann distribution concentrates on the states with lowest energy and finally when the temperature approaches zero only minimum energy states will have a probability of occurrence.

This physical annealing process has been simulated to handle optimization problems and an algorithm has been proposed by Kirkpatrick [1]. Later on this algorithm has been applied to several areas of optimization one being the economic load dispatch problem.

3.2. Simulated Annealing Based Economic Load Dispatch Algorithm

Step1: Select a set of initial power loadings for all the **n** generators such that the constraints on generator outputs are satisfied. Set the initial control perameter (Temperature, T) to a high value.

Step2: For a prespecified no of trials(**m**) in the chain of neighborhood solutions in that iteration determine the best loadings of all the generators in the neighborhood of current load settings by the following steps:

(a) Select a generator, s randomly as a dependent generator.

(b) From the known current loadings of the generators calculate loading on s, $\mathbf{p_s}$ using power balance constraint as,

$$p_s = D + P_L - \sum_{i=1, i\neq s}^{n} p_i \tag{3.2}$$

Where $\mathbf{p_s}$ represents output of selected generator. Vector $\mathbf{P}^{(m,T)}$ represents the generations of remaining **n-1** generators. Calculate cost, $\mathbf{F}^{(T)}$ with these generation values.

(c) Generate a neighborhood vector $\mathbf{N}^{(m,T)}$.

(d) Form new power loadings,

$$P_{new}^{(m.T)} = P^{(m,T)} + N^{(m,T)}$$

$$P_{s_{new}} = D + P_L - \sum_{i=1, i\neq s}^{n} p_{i_{new}} \tag{3.3}$$

(e) If the power loadings don't satisfy operating limits, then go for next trial, **m=m+1**

(f) If they are in limits then find out whether they satisfy various functional inequalities. If not go for next trial, **m=m+1**

(g) If the new power loadings satisfy all the constraints then find out new cost, $F^{(T)}_{new}$.

(h) Calculate change in the fuel cost,

$$\Delta F^{(T)} = F_{new}^{(T)} - F^{(T)} \tag{3.4}$$

(i) Check whether the new power generations can be accepted or not using Metropoli's acceptance criterion [11],

(1) If $\Delta F^{(T)} \le 0$, accept the new loads,

$$P^{(m,T)} = P_{new}^{(m,T)}$$
$$p_s^{(m,T)} = p_{s\,new}^{(m,T)} \tag{3.5}$$

(2) If $\Delta F^{(T)} > 0$...then find the Boltzmann probability factor,

$$P(\Delta F^{(T)}) = \frac{1}{1+\exp(\frac{-\Delta F^{(T)}}{k_B T})} \tag{3.6}$$

(3) If $P(\Delta F^{(T)}) < \text{random}(0,1)$, then also accept the new loadings as in the previous step. Else reject the new loadings.

Step3 : Update the control perimeter (Temperature, T) as per the decided cooling schedule.

Step4 : If **T** reached the minimum **T**, then stop.

Else go to **Step2**

3.3.Brief Description about the Steps Involved in Simulated Annealing Algorithm

3.3.1. Generation of a Neighborhood Solution

The optimization process will be affected greatly by the way we search for a solution in the neighborhood of the present solution, in each iteration. At any iteration **k**, the vector **P** holds the loadings of **n-1** generators. To find a solution in the neighborhood of **P**

the amount of perturbation for each loading is found according to a Gaussian probability distribution function.[4,12], whose standard deviation is set to the product of the control variable **T** and a scaling factor, γ., which means that the probability of generating a perturbation of the amount in the range between $-\gamma$**T** and $+\gamma$**T** is 68.26%.If the perturbation vector is stored in **N** then the new neighborhood solution becomes **(P+N)** and the power loadings of the dependent generator can be calculated using the equation (3.2).

3.3.2. Selection of Cooling Schedule

Selection of a cooling schedule involves the selection of,

- Initial value of temperature, $\mathbf{T_0}$
- Final value of temperature
- The rule of changing current temperature to the next one

Initially selection of a high value for **T** allows the Gaussian distribution to pick up solutions in a wide range(as the spread γ**T** will be high) so that the cost functions of higher values can be accepted. Consequently as the temperature, **T** reduced gradually it is possible for the solution to jump out of the local optimum points. As the value of **T** becomes very small the disturbance in the current solution becomes very low and finally the loadings remain almost constant. However the initial temperature should not be too high as it will generate a large number of unfeasible solutions in a very large neighborhood space. In the present work the results were compared with several initial temperatures.

The rate of cooling in the annealing process can be controlled by a number of different schedules [10,11]. In this work a simple exponential decay rate schedule has been used [11].

$$\mathrm{T}_{t+1} = \beta.\mathrm{T}_{t} \tag{3.7}$$

where $\mathrm{T_t}$ is the temperature at step **t** and $0 < \beta < 1$ is the constant cooling rate. In the physical annealing process the temperature must be lowered slowly to allow the solid to

reach equilibrium after each temperature drop. Otherwise undesired alignments may occur in the solid which can result in a meta stable structure rather than stable low energy structure. The same analogy works in simulated annealing also. The final low energy state depends on the cooling schedule to a greater extent. In this work, results obtained from several cooling schedules have been compared.

3.3.3. Acceptance Criteria

Simulated annealing uses probabilistic acceptance criteria for accepting the states obtained in each schedule. It is this criteria which actually makes it come out of the local optimum and reach global optimum.

It always accepts a state with low energy. It also accepts a high energy state. but in a limited way. Metropolis proposed [11] a probabilistic acceptance criteria to accept higher energy states which has been described in Step 2.(i.). From this step we can note that initially when the temperature is very high, if $\Delta F > 0$, the Boltzmann probability factor becomes almost ½, which implies that the probability of accepting the higher energy state initially is almost 50%. As the temperature decreases this probability increases and so the acceptance of higher energy state decreases and finally the probability becomes near 1 and the acceptance of higher energy state becomes almost 0.

3.4. Simulation Results and Discussion

The discussed method has been tested on several problems, which have been discussed in Chapter 2. The problems have also been tested with different cooling schedules and the results are compared.

The variation of cost function and the loadings on generators with respect to the control perameter, temperature have been shown in Fig.3.1-3.29 for all the problems.

3.4.1. Three Generator Problem

The discussed methodology has been first applied on a simple problem which consists of three generators [6] with simple quadratic cost functions and uses the simplified B-loss

formula to calculate the losses. The constraints applied being the power balance constraint and the operating limits on generators.

Case 1

Table 3.1. Data of cost coefficients and the power limits on generators for problem 3.4.1.

Unit	A	B	C	P_{min}	P_{max}
1	561	7.92	0.001562	150	600
2	310	7.85	0.00194	100	400
3	78	7.97	0.00482	50	200

Where A,B and C represent the cost coefficients. The units of each being, \$/h, \$/MW.h and \$/MW^2.h respectively. P_{min} and P_{max} are the power limits of generators.

Case 2

All the conditions are same as in case 1 except that the cost function for unit 1 becomes

$$C1 = 0.00128\, P_1^2 + 6.48\, P_1 + 459 \text{ [\$/h]}$$

Case 3

All the conditions are same as in case 1 except that the system in this case includes losses also. The losses have been calculated using simplified B-loss formula given by

$$P_L = 0.00003\, P_1^2 + 0.00009\, P_2^2 + 0.00012\, P_3^2 \text{ [MW]} \tag{3.8}$$

The problem in case1 has been studied with different combinations of cooling schedule and spread factor. Only the one which has given best results have been applied to the remaining cases.

(2.5), (2.8) and (2.10) give the cost function and the constraints to solve this problem.

Simulation Results For Various Cooling Schedules

Table 3.2. Simulation results of problem 3.4.1.(case1)for various cooling schedules

Case		P_1	P_2	P_3	Total power[MW]	Total cost [$/h]
T_0=10000 **γ = 0.01**	β					
	0.99	393.504	334.405	122.192	850	8194.356
	0.95	393.516	333.831	122.553	850	8194.381
	0.9	392.451	335.223	122.326	850	8194.562
	0.6	390.917	357.126	101.957	850	'8197.33
β=0.99 **γ = 0.01**	T_0					
	10000	393.504	334.405	122.192	850	8194.356
	10	595.448	106.473	148.078	850	8362.45
	100	549.501	167.044	133.454	850	8287.605
	1000000	393.232	334.36	122.307	850	8194.356
β=0.99 **T_0=10000**	γ					
	0.01	393.504	334.405	122.192	850	8194.356
	0.0001	548.997	167.653	133.35	850	8286.953
	0.1	394.231	333.752	122.017	850	8194.36
	1	386.022	323.276	140.701	850	8196.33

Results and Discussions

From the results it has been concluded that **T_0=10000,γ = 0.01** and **β=0.99** have produced best results. In the remaining two cases of this problem these values have been used to produce the results.

Table 3.3. Simulation Results of Problem 3.4.1.(case 2&3)

	P_1	P_2	P_3	Total power[MW]	Total cost [$/h]
Case 2	599.997	184.246	65.756	850	7252.88
Case 3	434.639	294.434	136.636	865.709 (loss=15.709)	8344.892

3.4.2.System With Piecewise Quadratic Cost Functions

Data for cost coefficients for piecewise quadratic cost function for a system with three connected subsystems, which contain different generation units, which use multiple fuels[5].

Table 3.4. Data of cost coefficients and the power limits of generators for problem 3.4.2.

S	U	Min	F_1	P_1	F_2	P_2	F_3	Max	F	A	B	C
1	1	100		196		250			1	0.2697E2	-.3975E0	.2176E-2
			1		2				2	0.2113E2	-.3059E0	.1861E-2
	2	50		114		157		230	1	0.1184E3	-.1269E1	.4194E-2
			2		3		1		2	0.1865E1	-.3988E-1	.1138E-2
									3	0.1365E2	-.1980E0	.1620E-2
	3	200		332		388		500	1	0.3979E2	-.3116E0	.1457E-2
			1		3		2		2	-0.5914E2	.4864E0	.1176E-4
									3	-0.2876E1	.3389E-1	.8035E-2
	4	99		138		200		265	1	0.1983E1	-.3114E-1	.1049E-2
			1		2		3		2	0.5285E2	-.6348E0	.2758E-2
									3	0.2668E3	-.2338E1	.5935E-2
2	5	190		338		407		490	1	0.1392E2	-.8733E-1	.1066E-2
			1		2		3		2	0.9976E2	-.5206E0	.1597E-2
									3	-0.5399E2	.4462E0	.1498E-3
	6	85		138		200		265	1	0.5285E2	-.6348E0	.2758E-2
			2		1		3		2	0.1983E1	-.3114E-1	.1049E-2
									3	0.2668E3	-.2338E1	.5935E-2
	7	200		331		391		500	1	0.1893E1	-.1325E0	.1107E-2
			1		2		3		2	0.4377E2	-.2267E0	.1165E-2
									3	-0.4335E3	.3559E0	.2454E-3
3	8	99		138		200		265	1	0.1983E1	-.3114E-1	.1049E-2
			1		2		3		2	0.5285E2	-.6348E0	.2758E-2
									3	0.2668E3	-.2338E1	.5935E-2
	9	130		213		370		440	1	0.8853E2	-.5675E0	.1554E-2
			3		1		2		2	0.1530E2	-.4514E-1	.7033E-2
									3	0.1423E2	-.1817E-1	.6121E-2
	10	200		362		407		490	1	0.1397E2	-.9938E-1	.1102E-2
			1		3		2		2	-0.6113E2	.5084E0	.4164E-4
									3	0.4671E2	-.2024E0	.1137E-2

Here F_1, F_2 and F_3 are the fuels that have to be used by each generator depending on its output. P_1 and P_2 are the intermediate power levels for the generator. If the generator output falls between P_{min} and P_1 the fuel F_1 has to be used by the generator. If it is between P_1 and P_2 then fuel F_2 has to be used. If the power level crosses P_2 then the fuel F_3 has to be used by the generator. So depending on the power range of each generator its fuel type and also its cost characteristic will change. Thus variation in powers render discontinuity in the cost characteristics used by the generators.

The cost function and the constraints for this problem have been given in chapter2, (2.7), (2.8) and (2.11)

This problem has also been tackled just as in the case of a simple system with continuous cost functions. The only difference here in this problem is, while calculating the cost **F** involved in each iteration, it has been observed for the loadings on generators. Depending on which generator is in which fuel region, the corresponding cost function of that fuel has been used for cost calculation. The cost function and the constraints, which are used in problem 3.4.1 will still work for this problem.

The above system has been tested for different loading conditions. As in the previous case, the best values of cooling schedule that fit for the first loading has been used for the remaining loadings.

Case1 deals with a net loading of 2400MW

Case2 deals with a net loading of 2500MW

Case 3 deals with a net loading of 2600MW

Case4 deals with a net loading of 2700MW

Case1 Total Load Applied is 2400 MW

Table 3.5. Simulation results of problem 3.4.2.(case 1) for various cooling rates

S	U	F	$\gamma = 0.01$, $T_0 = 10000$ β			
			0.99	**0.98**	**0.9**	**0.6**
1	1	1	189.524	190.183	142.791	129.097
	2	1	202.421	202.511	177.418	107.847
	3	1	254.087	256.365	260.641	385.354
	4	3	232.793	233.012	167.183	109.124
2	5	1	242.214	234.66	446.14	413.979
	6	3	233.014	233.051	125.45	90.1024
	7	1	252.856	266.892	289.502	396.521
3	8	3	232.979	233.128	115.21	99.5
	9	1	320.188	313.206	365.798	375.703
	10	1	239.907	236.993	309.866	297.772
Total load			2400	2400	2400	2400
Total cost			481.724	482.08	574.225	1545.06

Table 3.6. Simulation results for problem 3.4.2.(case 1) for various initial temperatures.

S	U	F	$\gamma = 0.01$, $\beta = 0.99$ T_0			
			10	**100**	**10000**	**1000000**
1	1	1	189.567	195.9145	189.541	185.245
	2	1	194.382	202.999	202.421	198.0165
	3	1	252.974	248.656	254.087	257.3755
	4	3	236.651	235.235	232.793	228.053
2	5	1	235.234	253.729	242.214	246.512
	6	3	222.628	233.314	233.014	238.868
	7	1	258.759	250.421	252.856	252.084
3	8	3	231.191	234.5714	232.979	233.5
	9	1	323.853	310.186	320.188	315.097
	10	1	254.761	234.975	239.907	245.248
Total load			2400	2400	2400	2400
Total cost			483.09	482.233	481.724	482.319

Table 3.7. Simulation results for problem 3.4.2.(case 1) for various spread factors.

S	U	F	$T_0 = 10000$, $\beta = 0.99$ γ			
			0.0001	**0.01**	**0.1**	**1**
1	1	1	127.336	189.541	190.571	191.396
	2	1	114.907	202.421	202.22	200.675
	3	1	404.518	254.087	254.772	251.618
	4	3	107.131	232.793	233.132	229.717
2	5	1	383.877	242.214	240.197	249.039
	6	3	131.075	233.014	233.213	234.877
	7	1	364.085	252.856	253.957	246.522
3	8	3	127.045	232.979	232.842	234.612
	9	1	353.47	320.188	320.275	317.87
	10	1	286.556	239.907	238.821	243.675
Total load			2400	2400	2400	2400
Total cost			614.059	481.724	481.729	481.984

Here **F** indicates the fuel used by each unit in the best case results.

Conclusions

In this problem also it has been observed that $\mathbf{T_0 = 10000}$, γ = **0.01** and **β=0.99** have given best results. For the remaining loading conditions also these values have been used to obtain the results.

Table 3.8. Simulation results for problem 3.4.2.(case 2,3&4).

S	U	2500 MW		2600 MW		2700 MW	
		F	Gen.	F	Gen.	F	Gen.
1	1	2	206.5399	2	216.099	2	226.572
	2	1	206.522	1	211.147	1	215.486
	3	1	265.8019	1	277.99	1	291.611
	4	3	235.96089	3	239.0749	3	242.3739
2	5	1	258.0937	1	275.895	1	292.847
	6	3	235.926	3	239.157	3	242.227
	7	1	268.934	1	287.061	1	302.514
3	8	3	235.7704	3	239.178	3	242.296
	9	1	331.32388	1	342.461	1	355.1022
	10	1	255.127	1	271.935	1	288.9867
Total load		2500		2600		2700	
Total cost		526.2389		574.3857		626.2545	

3.4.3. System With Emission Dispatch Constraints

The inclusion of emission considerations in dispatch scheduling actually modifies either the objective function or the set of constraints. Any optimization procedure can't minimize everything i.e. cost, fuel used, emission of pollutants etc. at a single time. If we go for the minimization of cost alone then the emission levels may be high. Otherwise if we go for minimization of emission levels then the cost may become high. So we need to have a compromise between these things. In this work, eight different dispatch strategies have been worked out, which have been presented in Table 3.9.

Table 3.9.Different strategies worked out in emission dispatch problem

No.	Dispatch strategy	Objective Function	Constraints
1.	Min Fuel Cost (Economic Dispatch)	$\sum_{i=1}^{N_g} F_i(P_i) * FP_i$	
2.	Minimum SO_2 Emission	$\sum_{i=1}^{N_g} SO2_i(P_i)$	
3.	Minimum NO_x Emission.	$\sum_{i=1}^{N_g} NOX_i(P_i)$	
4.	Minimum Fuel Use	$\sum_{i=1}^{N_g} F_i(P_i)$	
5.	Minimum fuel cost with.SO_2.Emission Limit	$\sum_{i=1}^{N_g} F_i(P_i) * FP_i$	$\sum_{i=1}^{N_g} SO2_i(P_i) \le L_{SO2}$
6.	Minimum fuel cost with NO_x Emission Limit	$\sum_{i=1}^{N_g} F_i(P_i) * FP_i$	$\sum_{i=1}^{N_g} NOX_i(P_i) \le L_{NOX}$
7.	Minimum fuel cost and SO_2 Emission value with SO_2 Emission limit.	$\sum_{i=1}^{N_g} [F_i(P_i) * FP_i + SO2_I(P_I) * EA_{value}]$	$\sum_{i=1}^{N_g} SO2_i(P_i) \le L_{SO2}$ $\sum_{i=1}^{N_g} SO2_i(P_i) \le EA^{Max}$
8.	Minimum Fuel Cost with SO_2 and NO_x Emission Limits	$\sum_{i=1}^{N_g} F'_i(P_i) * FP_i$	$\sum_{i=1}^{N_g} SO2_i(P_i) \le L_{SO2}$ $\sum_{i=1}^{N_g} NOX_i(P_i) \le L_{NOX}$

Note: All the dispatch strategies presented here will also include a load constraint and a generating unit constraint.

The first strategy presented in this table is the conventional minimum cost strategy. The second and the third strategies are minimum SO_2 and NO_x strategies respectively. These second and third strategies will give the minimum limits on the emission

of the pollutants below which we can't go and the first strategy gives the minimum cost below which we can't go. So to make a compromise between these cost and emission levels the maximum SO_2 emission level (L_{SO2}) has been taken as the average of the emission obtained by the strategies one and two. Similarly the maximum NO_x emission level (L_{NOX}) has been taken as the average of the emission obtained by the strategies one and three [9]. The fourth strategy provides an indication of the minimum total fuel use. The remaining dispatch strategies are based upon the minimum cost objective subjected to one or more emission levels. The seventh strategy minimizes the total of the operation cost and the estimated value of the SO_2 emission allowances taken from [9]. Finally eighth strategy includes both SO_2 and NO_x limits.

The pollutants actually will form functional inequality constraints on the power outputs of generators. While applying the algorithm discussed in 3.2. on the proposed strategies, the step2.(f.) in the algorithm, which will check for the functional inequalities, will be applied to check whether these emission of pollutants are in limits or not. All the remaining basic steps in the algorithm will remain same in the optimization of various strategies.

Also the cost characteristics used in this problem for fuel and emission of the pollutants are not quadratic but of the form

$$\text{COST} = C3\ P_I^3 + C2\ P_I + C0 \tag{3.9}$$

The units of cost will be \$/MBTU if the cost type is Fuel, it will be Tons if the cost type is SO2 or NOx. The discussed strategies have been implemented on a 3 plant, 9 unit test system with 6 hour load data [9].

The 6 hour load data for the system is,

Table 3.10. Load data for six continuous hours for problem 3.4.3.

Hour	1	2	3	4	5	6
Load (MW)	2000	1800	2150	2300	2500	2250

The cost and emission coefficients for the system being,

Table 3.11. Data of cost and emission coefficients and power limits for the problem 3.4.3.

Unit	P_{min} (MW)	P_{Max} (MW)	Fuel price ($/MBTU)	Eq type	C0	C1	C2
1	45.0	240.0	1.4	Fuel	7.59211E1	8.69354E0	4.75855E-6
				SO2	4.55526E-2	5.21612E-3	2.85514E-9
				NOx	5.07318E-2	4.31109E-4	1.47897E-8
2	45.0	240.0	1.4	Fuel	8.60796E1	8.68309E0	4.55527E-6
				SO2	5.16478E-2	5.20986E-3	2.73316E-9
				NOx	5.07318E-2	4.31109E-4	1.47897E-8
3	275.0	450.0	1.4	Fuel	2.2494E2	8.7515E0	1.31540E-6
				SO2	1.34964E-1	5.2509E-3	7.8924E-10
				NOx	3.2163E-1	2.9966E-5	6.14709E-9
4	150.0	350.0	1.75	Fuel	2.31141E2	7.34518	5.15577E-6
				SO2	1.38685E-1	4.4071E-3	3.09346E-9
				NOx	-9.3024E-2	7.77628E-4	8.64334E-9
5	150.0	350.0	1.75	Fuel	2.30881E2	7.23297E0	6.11535E-6
				SO2	1.38529E-1	4.33978E-3	3.6692E-9
				NOx	-9.3024E-2	7.77628E-4	8.64334E-9
6	350.0	750.0	1.75	Fuel	6.5E2	8.57E0	1.3E-6
				SO2	3.9E-1	5.142E-3	7.8E-10
				NOx	3.03952E-2	3.36485E-4	1.92622E-9
7	35.0	175.0	1.8	Fuel	5.32498E2	9.52691E0	4.4109E-6
				SO2	2.6625E-2	4.76346E-3	2.20546E-9
				NOx	1.05714E-1	1.30298E-3	1.4881E-9
8	35.0	175.0	1.8	Fuel	5.8249E1	9.28746E0	7.62027E-6
				SO2	2.91246E-2	4.64374E-3	3.81014E-9
				NOx	1.05714E-1	1.30298E-3	1.4881E-9
9	45.0	240.0	1.8	Fuel	1.73124E2	7.68484E0	1.39491E-5
				SO2	1.03874E-1	4.6109E-3	8.36946E-9
				NOx	2.04166E-2	4.0667E-4	1.44581E-8

All equations are of the form $C3\ P_I^3 + C2\ P_I + C0$

Also the value of emission allowance in each case for the six hours is $300.

The results obtained after applying the discussed simulated annealing method to the above problem have been presented here. All the values are the total values obtained after six hours. The results obtained by the best cooling schedule have been presented in table 3.12. The Tables 3.13 through 3.15 have been presented to show the variations in the results when there are variations in cooling schedule.

For $\beta = 0.99$, $\gamma = 0.01$ and $T_0 = 10000$

Table 3.12. Simulation results for problem 3.4.3. using best cooling schedule

Strategy	SO_2 limit (tons)	NO_x limit (tons)	Fuel (MBTU)	Cost ($)	SO_2 (tons)	NOx (tons)
Min Cost			122357	196493	72.557	18.853
Min SO2			122708	204263	70.699	17.727
Min NOx			123642	204296	71.925	15.978
Min Fuel			121841	198766	71.803	18.437
Min Cost with SO2 Limits	71.628		122333	199176	71.491	18.21
Min Cost with NOx Limits		17.4155	122752	199009	72.22	17.328
Min cost + emission allow with SO2 limits	71.628		122678	202411	71.626	16.62
Min cost with SO2 and NOx limits	71.628	17.4155	122799	201868	71.623	17.083

Results obtained due to various other cooling schedules are,

$\beta = 0.99$, $\gamma = 0.0001$ and $T_0 = 10000$

Table 3.13. Simulation results for problem 3.4.3.with variation in spread factor.

Strategy	Fuel (MBTU)	Cost ($)	SO_2 (tons)	NO_x (tons)
1	122533	198353	72.44	17.749
2	122817	204714	70.987	17.362
3	123608	204332	71.965	16.024
4	121983	200235	71.827	17.8258
5	122915	202601	71.702	16.9432
6	122740	200543	72.251	16.8336
7	122915	202601	71.8042	16.9432
8	122915	202601	71.8	16.9432

$\beta = 0.99$, $\gamma = 0.01$ and $T_0 = 100$

Table 3.14. Simulation results for problem 3.4.3. with variation in T_0

Strategy	Fuel (MBTU)	Cost ($)	SO_2 (tons)	NO_X (tons)
1	122859	200227	72.6443	17.605
2	122974	204458	71.4026	17.0651
3	123283	203467	72.086	16.8942
4	122600	201756	71.965	17.4656
5	123149	203678	72.0732	16.98
6	122876	201837	72.0567	17.2343
7	123149	203673	72.0732	16.98
8	123149	203678	72.0732	16.98

$\beta = 0.6$, $\gamma = 0.01$ and $T_0 = 10000$

Table 3.15. Simulation results for problem 3.4.3.with variation in β.

Strategy	Fuel (MBTU)	Cost ($)	SO_2 (tons)	NO_X (tons)
1	122757	200713	71.93	18.0067
2	123236	204352	71.8948	17.655
3	123054	202936	71.9853	17.4067
4	122636	202343	71.9449	17.6448
5	122929	202405	71.913	17.733
6	123144	201482	72.33	17.414
7	123066	202807	71.907	17.4746
8	123011	202399	71.9145	17.452

3.4.4. Problems with Prohibited Zones, Spinning Reserves and Fixed Base Generation Levels

Due to physical restrictions of power plant components, generating units may have prohibited operating zones lying between their minimum and maximum operating powers. Operating in those zones may result in amplification of vibrations in a shaft bearing, which should be avoided in practical applications. Usually these isolated subregions will separate the decision space into disjoint subsets that constitute a nonconvex decision space. Therefore the corresponding economic load dispatch problem becomes a nonconvex optimization problem which is a challenging task to tackle. Apart from these if there are spinning reserves and

Simulated annealing as a combinatorial optimization technique can tackle such a complex problem with multiple decision spaces. The algorithm discussed in section 3.2. can also be applied to this problem. The only variation being, when the new powers are accepted in step2. (f.) of the algorithm, it has been also checked whether the powers fall in prohibited zones. If so the new powers have been rejected and the algorithm proceeds for the selection of some other new power loadings.

The discussed methodology has been applied on three different types of systems with prohibited zones, spinning reserves and fixed base case generations. As in the previous problems different cooling schedules have been applied to the first case and the one, which produced best results have been used for the remaining cases.

Case1

In this the methodology has been applied on a 15-unit system [7,8] with 4 units having prohibited zones. The system supplies a demand of 2650MW and provides a spinning reserve of 200MW. Before applying the strategy the spinning reserve contribution of the units have been calculated by using the strategy discussed in [7]

$$S_i = \mathrm{MIN}\ \{\ (P_{imax} - P_i)\ ,\ S_{imax}\ \} \qquad (3.10)$$

Where S_i = spinning reserve of unit i

P_{imax} = max generation limit of unit i

S_{imax} = the maximum spinning reserve of unit i

Using these spinning reserves the effective upper generation limits have been fixed and the obtained values have been directly used to apply the discussed methodology.

Input data for the 15-unit system is,

Table 3.16. Input data for problem 3.4.4.(case1)

Unit	A	B	C	P_{imin}	P_{imax}	S_{imax}	Effective P_{imax}	S_I
1.	671.03	10.07	0.000299	150	455	50	455	0
2	574.54	10.22	0.000183	150	455	0	455	0
3	374.59	8.8	0.001126	20	130	30	130	0
4	374.59	8.8	0.001126	20	130	30	130	0
5	461.37	10.4	0.000205	150	470	0	470	0
6	630.14	10.1	0.000301	135	460	0	460	0
7	548.2	9.87	0.000364	135	465	50	465	0
8	277.09	11.5	0.000338	60	300	50	250	50
9	173.72	11.21	0.000807	25	162	30	160	0
10	175.95	10.72	0.001203	20	160	30	160	0
11	186.86	11.21	0.003586	20	80	20	60	20
12	230.27	9.9	0.005513	20	80	0	80	0
13	225.28	13.12	0.000371	25	85	20	65	20
14	309.03	12.12	0.001929	15	55	40	15	40
15	323.79	12.41	0.004447	15	55	40	15	40

The prohibited zones of generators for this problem are,

Table 3.17. Prohibited zones of units for problem 3.4.4.(case1)

Unit	Zone 1 (MW)	Zone 2 (MW)	Zone 3 (MW)
2	[185,225]	[305,335]	[420,450]
5	[180,200]	[260,335]	[390,420]
6	[230,235]	[365,395]	[430,455]
12	[30,55]	[65,75]	

In tables 3.18 through 3.19, results obtained after applying Simulated Annealing technique to problem 3.4.4.(case1) using various cooling schedules have been presented. As in the previous case, the schedule, which produces best results has been used for the remaining two types of problems discussed in case 2 and case 3.

Case 2

In this a 5 unit system with identical polynomial cost characteristics and operating limits have been taken [7] to demonstrate the effectiveness of the Simulated Annealing method

The cost function for each generator is given by,

$$F_i(P_i) = 350 + 8 * P_i + 0.001 * P_i^2 + 10^{-6} * P_i^3 \ (\$/hr) \quad (3.11)$$

the operating limits are

$$120 \text{ MW} < P_i < 450 \text{ MW}, i = 1, 2, 3, 4, 5$$

the load applied on the system is 1175MW.

Case 3

In this case the same 5-unit system as in case2 has been used. The only difference being, the units 4 and 5 have been fixed at a base generation level of 320MW. This makes the system further complicated. Because these two units are undispatchable and so the feasible region becomes still narrow.

The total demand applied on the system in this case is 1552MW.

The prohibited zones of the generators for these cases 2 & 3 have been given in Table3.20.

Simulation results of problem 3.4.4.(case 1) for various cooling schedules have been presented in tables 3.18 and 3.19. Table 3.18 shows the variations in results due to spread factor and due to the cooling rate. Table 3.19 shows the variations in results due to change in initial temperatures.

Table 3.18. Simulation Results of problem 3.4.4.(case1) for various γ, β

Unit	**$T_0 = 10000$, $\beta = 0.99$** γ			**$\gamma = 0.01$, $T_0 = 10000$** β		
	0.0001	**0.01**	**1**	**0.6**	**0.9**	**0.99**
1	307.245	453.754	405.729	315.16	279.135	453.754
2	455	419.615	451.075	365.545	453.614	419.615
3	129.995	129.922	128.532	129.893	122.079	129.922
4	129.982	129.929	129.014	77.3439	129.974	129.929
5	456.034	433.0738	440.26	426.912	444.028	433.0738
6	360.141	364.9105	419.227	404.71	346.592	364.9105
7	439.732	463.168	460.738	398.899	366.81	463.168
8	109.607	60.0416	60.4659	157.312	204.16	60.0416
9	25.0043	25.001	25.4626	118.584	73.716	25.001
10	103.853	20.297	24.8052	119.931	95.7443	20.297
11	20.0042	20.0637	20.7773	20.5536	20.0773	20.0637
12	58.3911	75.203	28.9036	60.1496	59.0692	75.203
13	25.0109	25.02	25.0107	25.0071	25.0002	25.02
14	15	15	15	15	15	15
15	15	15	15	15	15	15
Total load	2650	2650	2650	2650	2650	2650
Total Cost	32736.8	32620	32624.8	32964.9	32920.8	32620

Table 3.19. Simulation results of problem 3.4.4.(case1) for various initial temperatures

Unit	$\gamma = 0.01$, $\beta = 0.99$ T_0		
	100	10000	1000000
1	346.295	453.754	454.998
2	454.96	419.615	419.791
3	129.951	129.922	129.991
4	129.985	129.929	129.923
5	454.064	433.0738	389.688
6	364.955	364.9105	364.941
7	428.796	463.168	464.942
8	123.367	60.0416	60.1142
9	25.0171	25.001	25.0299
10	60.377	20.297	70.5508
11	20.1021	20.0637	20.0234
12	57.075	75.203	64.9504
13	25.057	25.02	25.0571
14	15	15	15
15	15	15	15
Total load	2650	2650	2650
Total Cost	32727	32620	32622

Table 3.20. Prohibited zones on the units for problem 3.4.4.(case 2 & 3)

Unit	Zone 1	Zone 2
1	[240,275]	[315,375]
2	[210,275]	[300,390]
3	[200,250]	[290,370]

From the results it has been observed that the spread factor, $\gamma = 0.01$, cooling rate, $\beta = 0.99$ and an initial temperature, $T_0 = 10000$ are producing best results in this case also. So these values have been used to tackle the remaining two cases of problem 3.4.4.

Table 3.21. Simulation results of problem 3.4.4.(case 2)

Unit	Results without taking prohibited zones into account P (MW)	Results taking prohibited zones into account P (MW)
1	235.191	275.006
2	233.598	209.994
3	236.222	199.9973
4	234.73	246.5969
5	235.259	243.4046
Total load	1175	1175
Total Cost	11491	11497.2568

Note: the total load applied in this case is 1175MW

Table 3.22. Simulation results of problem 3.4.4.(case 3)

Unit	Results without taking prohibited zones into account P (MW)	Results taking prohibited zones into account P (MW)
1	304.245	239.958
2	303.747	390.0119
3	304.008	282.0291
4	320	320
5	320	320
Total load	1552	1552
Total Cost	14797.9	14821.1406

Note: the total load applied in this case is 1552MW

3.5. Conclusions

From the various results it has been observed that the cooling schedule do effect the working of the algorithm. From the variations in initial temperature, it can be observed that, there is not much difference in the results when they are tested with $\mathbf{T_0}$ = 10000 and 1000000. From this one can say that the selection of a very high initial temperature unnecessarily goes through lot of local minimum points. Also it can be observed that with a low initial temperature, there is a possibility of the solution getting trapped at local minimum.

The spread factor (γ) which determines the random search region also affects the final solution to a greater extent. A very low value of γ confines the search procedure to a small region, which might make the solutions stay at local minimum only. Also a large value of γ unnecessarily starts its search procedure at a region which is well outside the feasible region.

From the results it can also be observed that, a steady cooling rate always gives better results. The steep cooling rate like 0.6 almost failed to give any results. Even though there is not much difference in the results obtained from β= 0.99 and 0.95, we can observe from the graphs that, for β = 0.95, the results are not still properly converged.

From these observations it can be concluded that $\mathbf{T_0 = 10000}$, $\boldsymbol{\beta = 0.99}$ and $\boldsymbol{\gamma = 0.01}$ gives proper results.

So once a proper cooling schedule has been selected for the problem, then Simulated Annealing can be applied to the problem to obtain best results. Even though the algorithm takes longer time, as it is a random search procedure, we can observe many advantages of applying Simulated Annealing to Economic Load Dispatch problem. The main advantage being that we can meet the load demand and transmission losses exactly. The other advantages are that the method can handle all types constraints and cost functions, which we can observe from the problems 3.4.2., 3.4.3. and 3.4.4.

In fact we can observe from the tables 3.21. and 3.22. that the Simulated Annealing method perfectly updates the powers according to the gradients of the cost functions, as suggested by the Lagrange's method. Because when the cost characteristics are same and when there are no prohibited zones in problem 3.4.4. (Case 2 & 3), the powers of the individual generators obtained by Simulated annealing algorithm are almost equal, which should be, according to Lagrange's method.

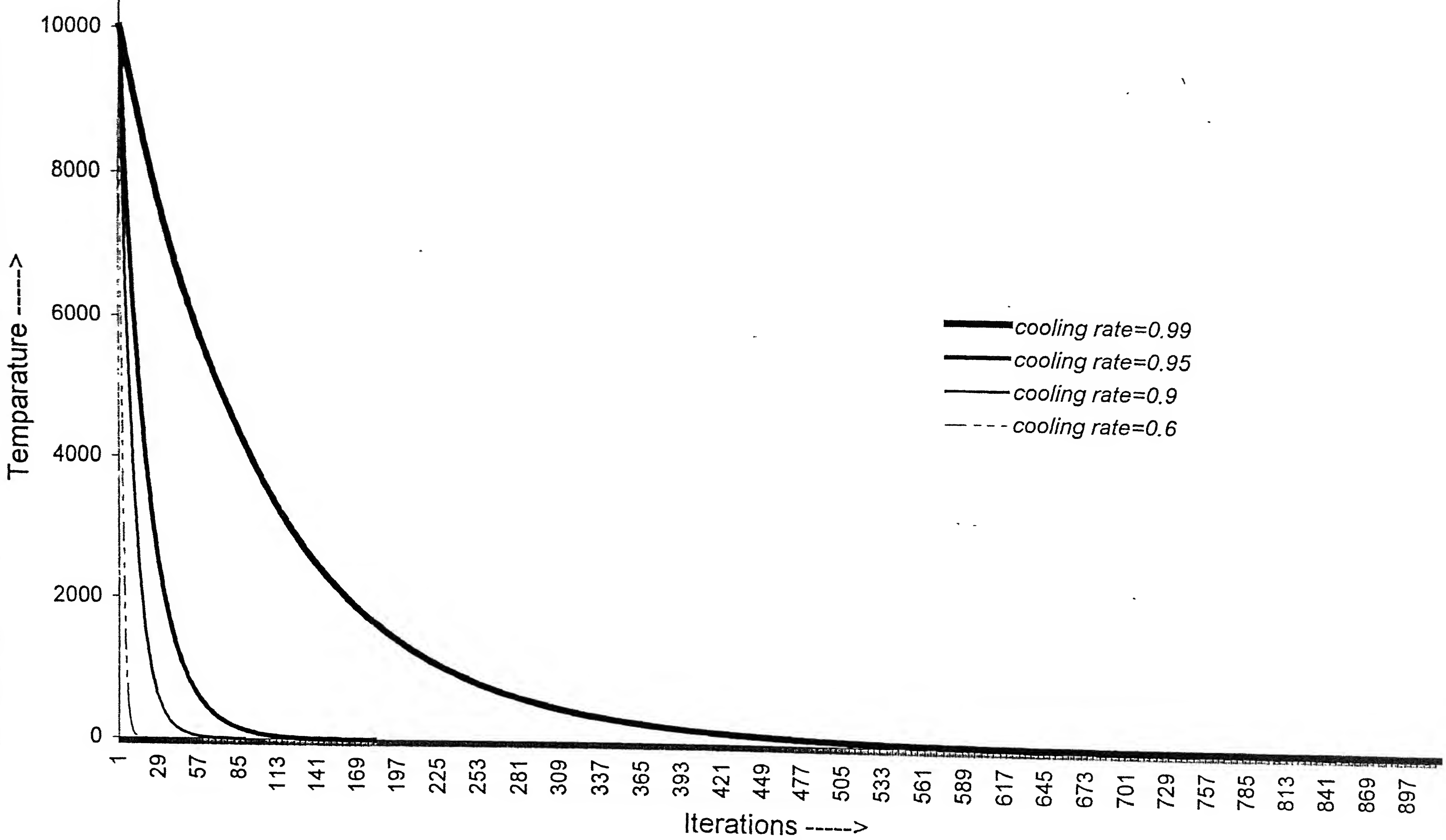


Fig.3.1.VARIOUS COOLING SCHEDULES USED

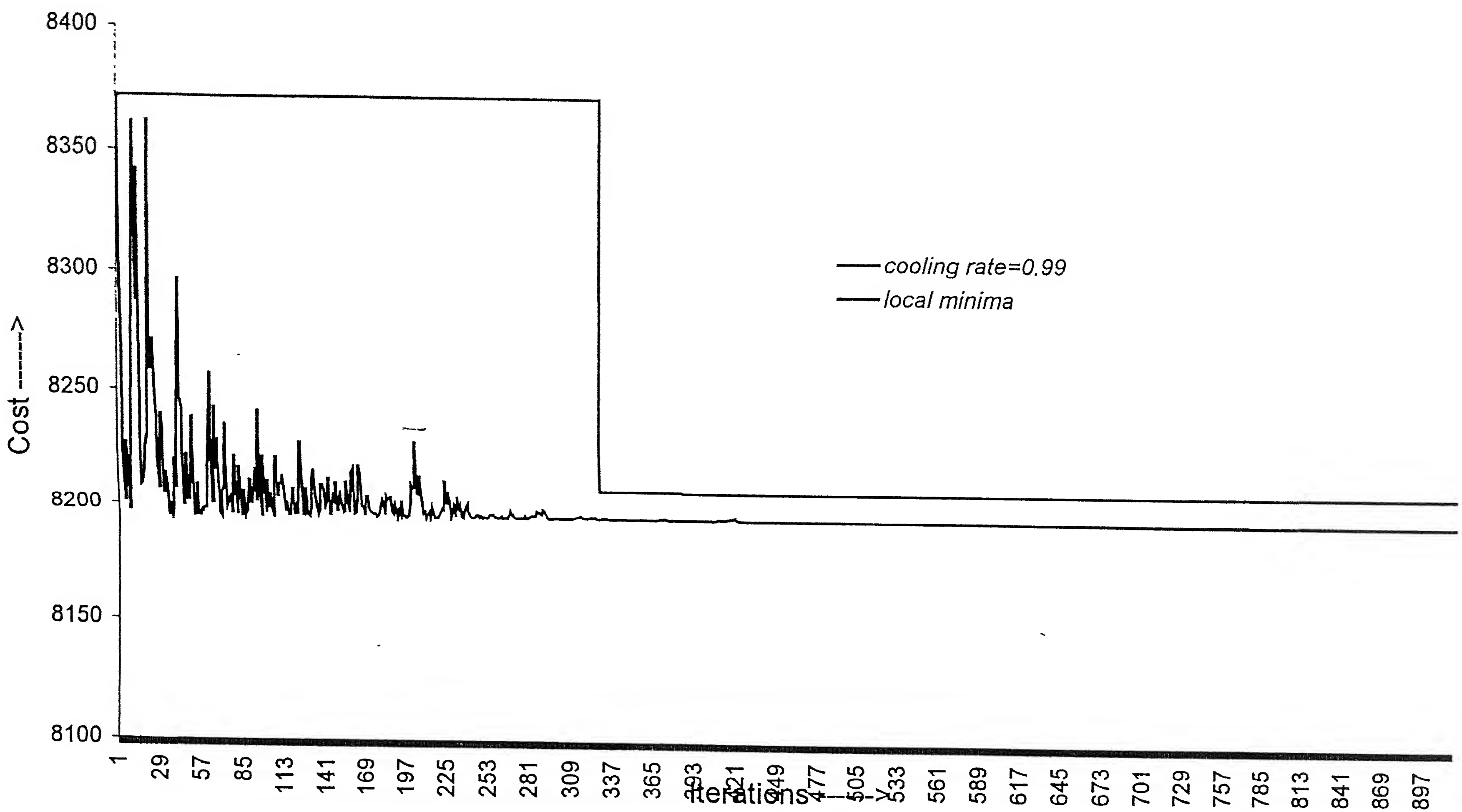


Fig.3.2.VARIATION OF COST FOR BEST COOLING RATE FOR PROBLEM 3.4.1(CASE1)

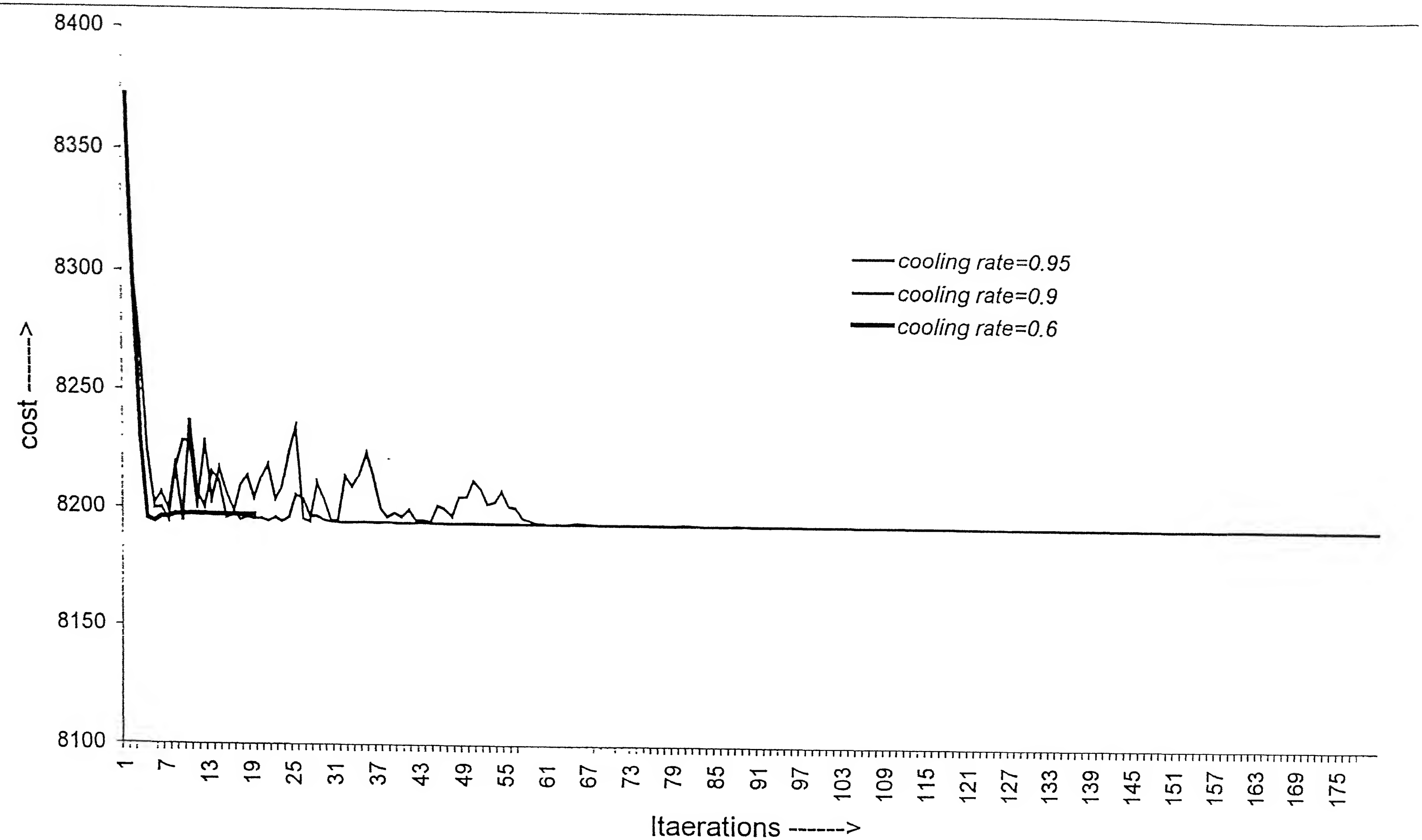


Fig3.3.VARIATION OF COST FOR VARIOUS COOLING RATES FOR PROBLEM 3.4.1(CASE1)

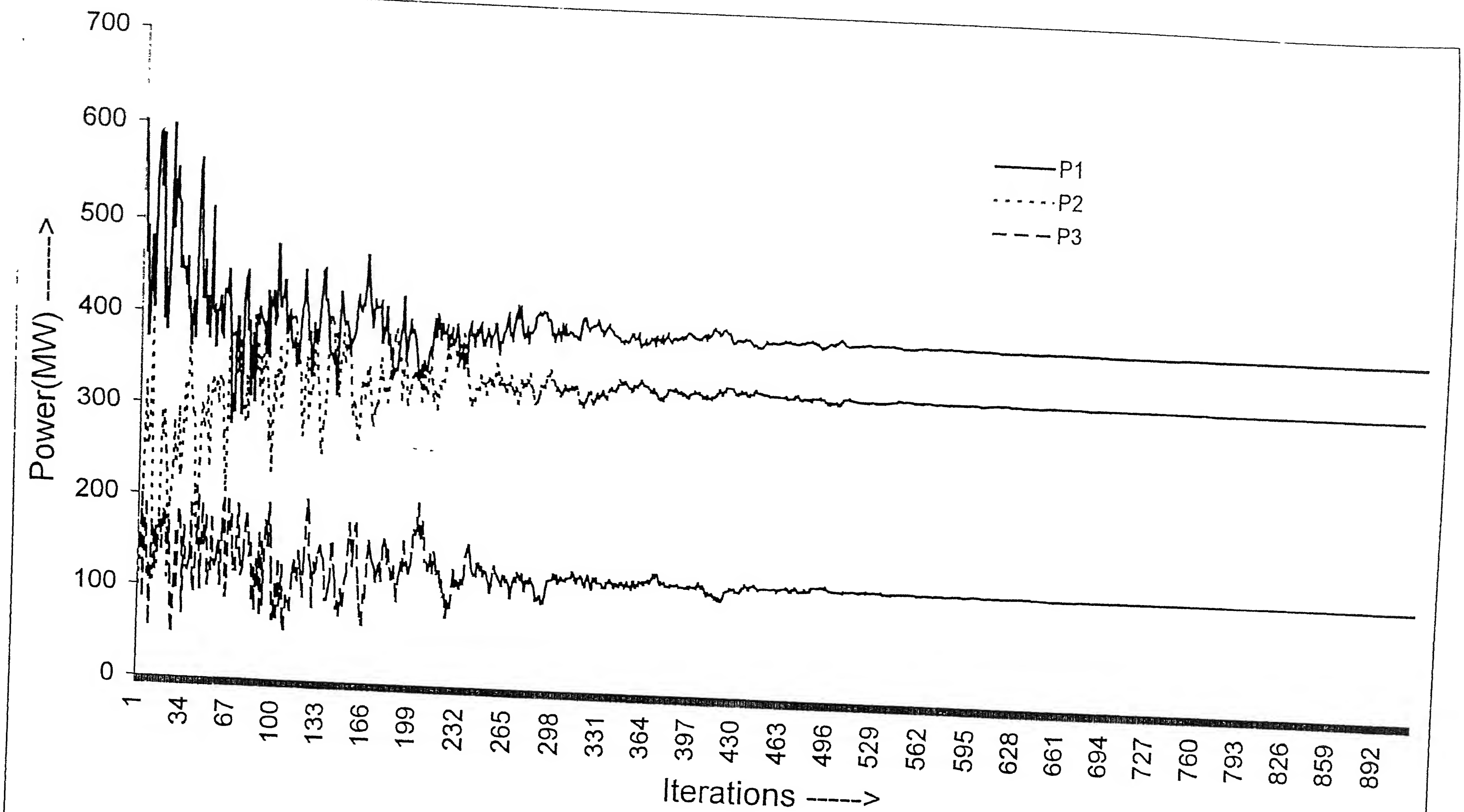


Fig.3.4.VARIATION OF POWERS FOR PROBLEM 3.4.1(CASE 1) WITH BEST COOLING SCHDULE

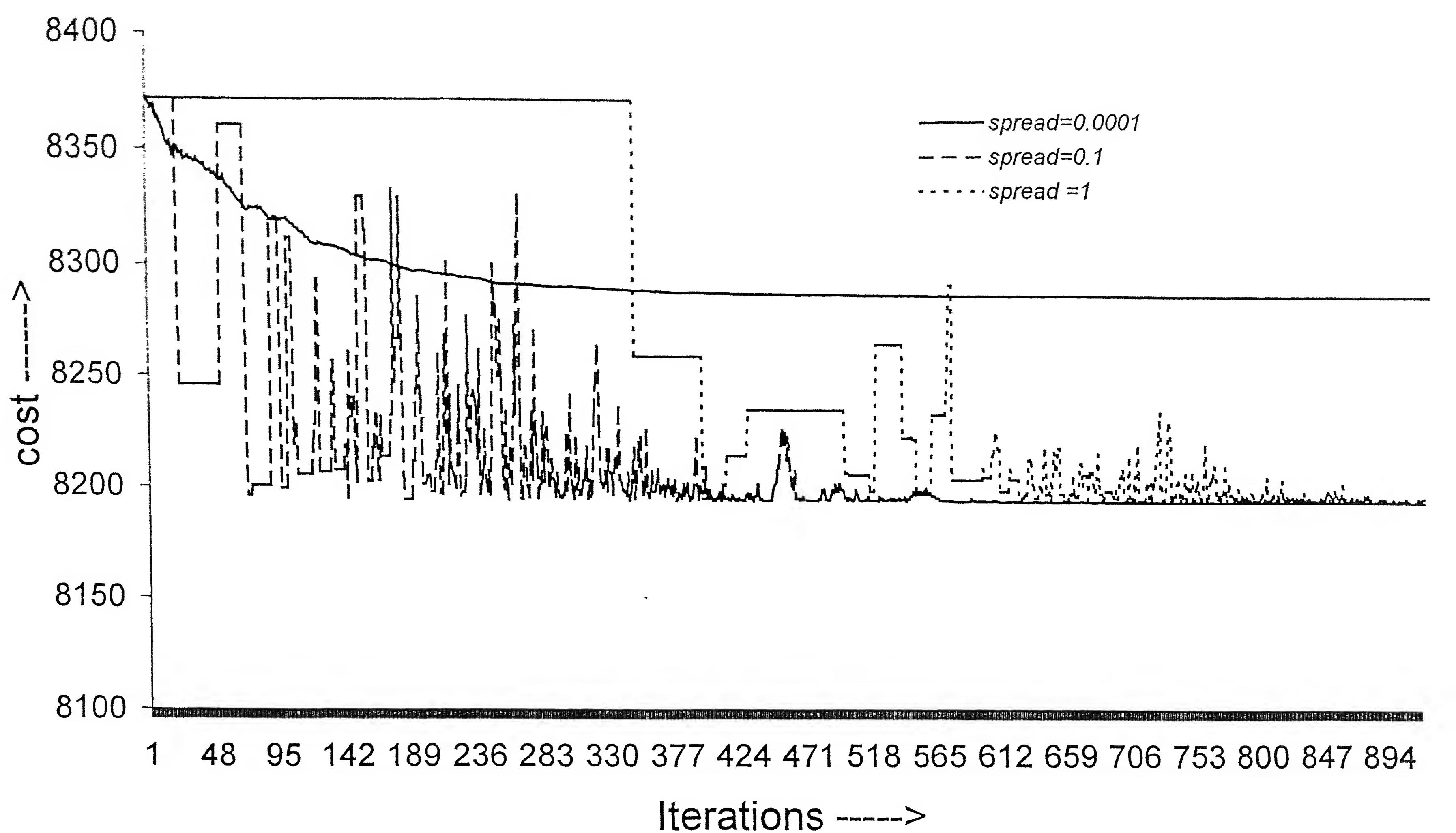


Fig.3.5.VARIATION OF COST FOR DIFFERNT SPREAD FACTORS FOR PROBLEM 3.4.1(CASE1)

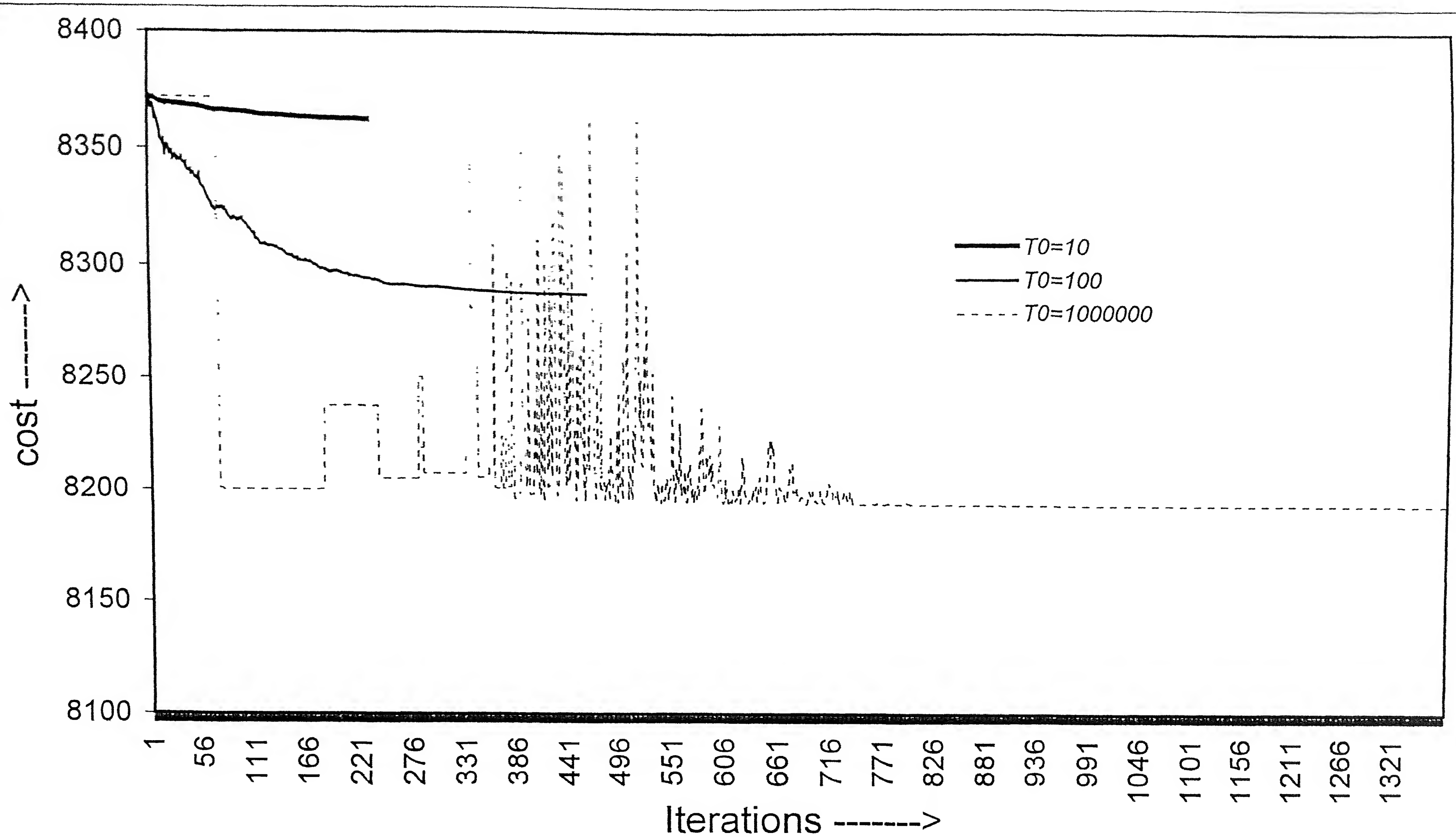


Fig.3.6.VARIATION OF COST WITH DIFFERENT INITIAL TEMPARATURES FOR PROBLEM3.4.1(CASE1)

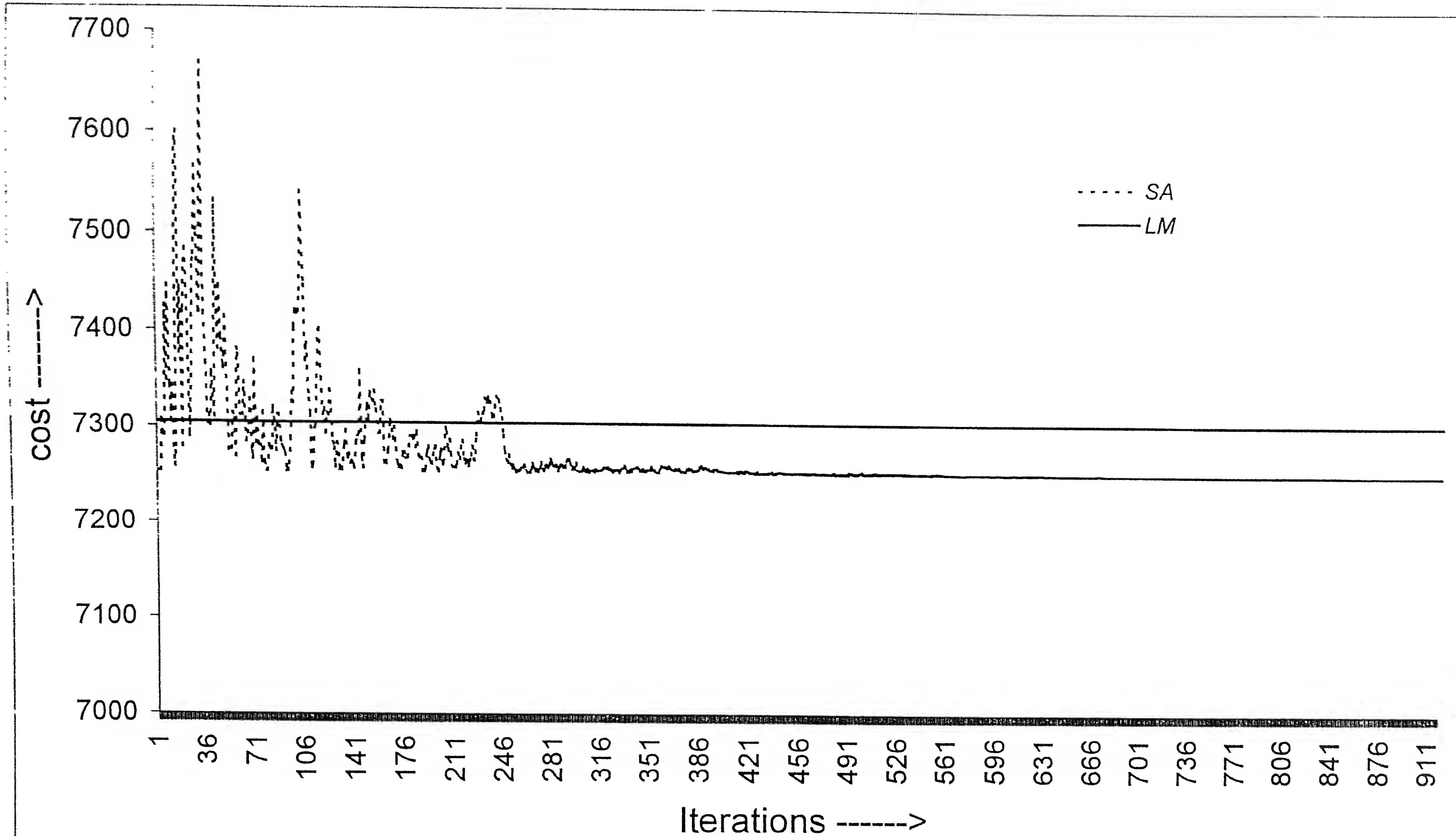


Fig.3.7.VARIATION OF COST OF PROBLEM 3.4.1(CASE2) WITH BEST SCHEDULE

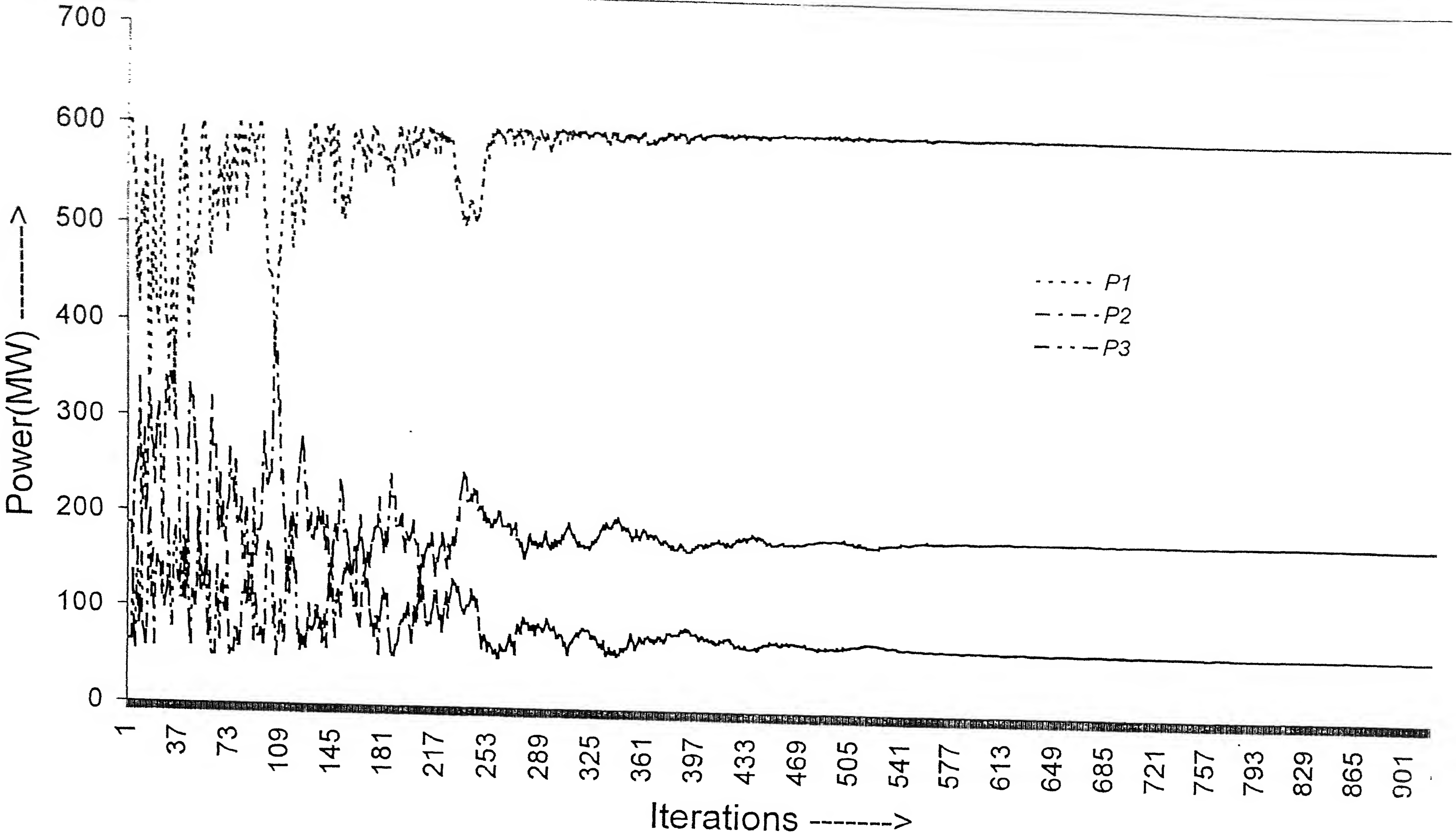


Fig.3.8.VARIATION OF POWERS FOR PROBLEM 3.4.1(CASE2) USING BEST COOLING SCHEDULE

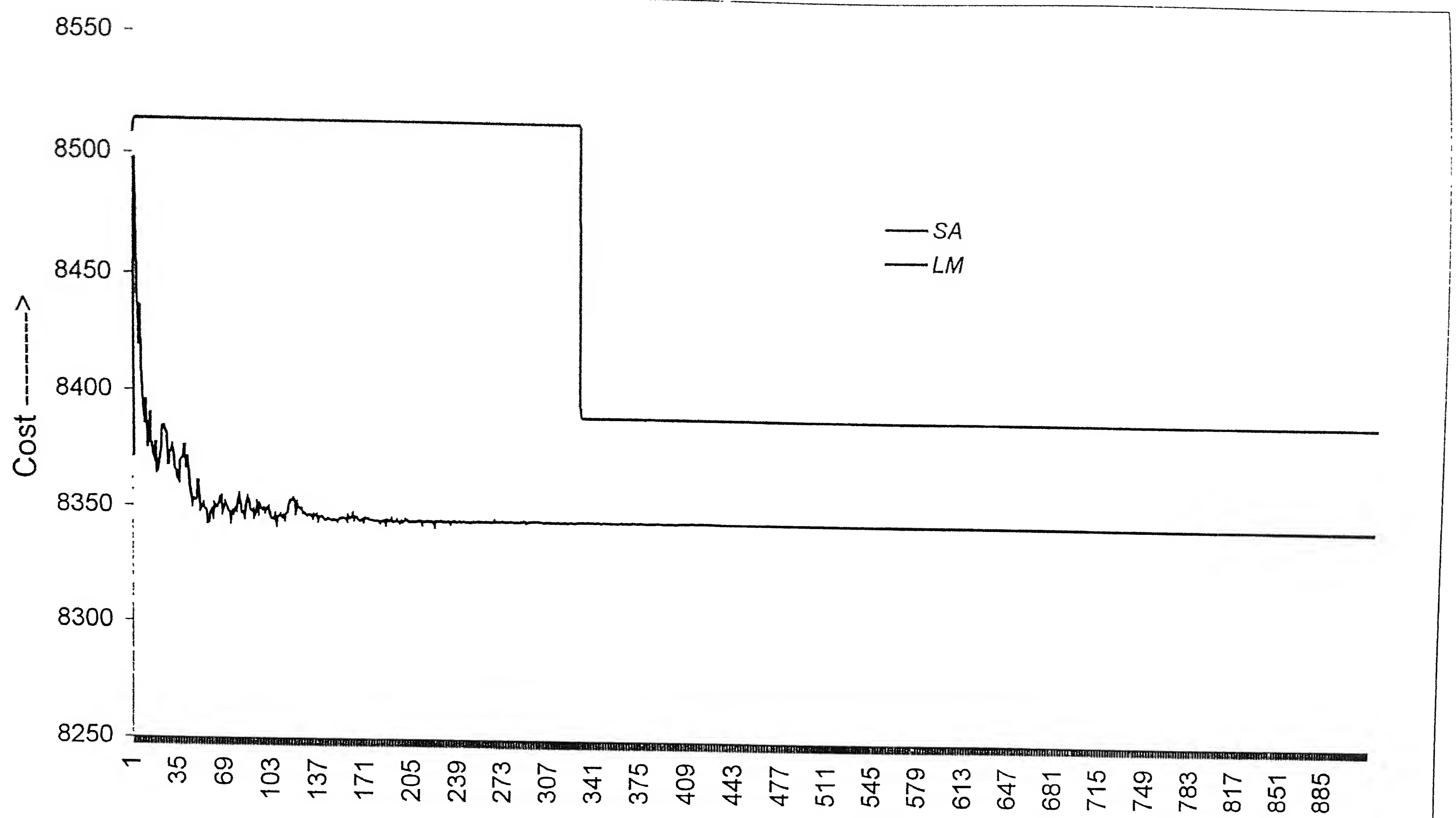


Fig.3.9.VARIATION OF COST FOR PROBLEM 3.4.1(CASE3) USING BEST COOLING SCHEDULE

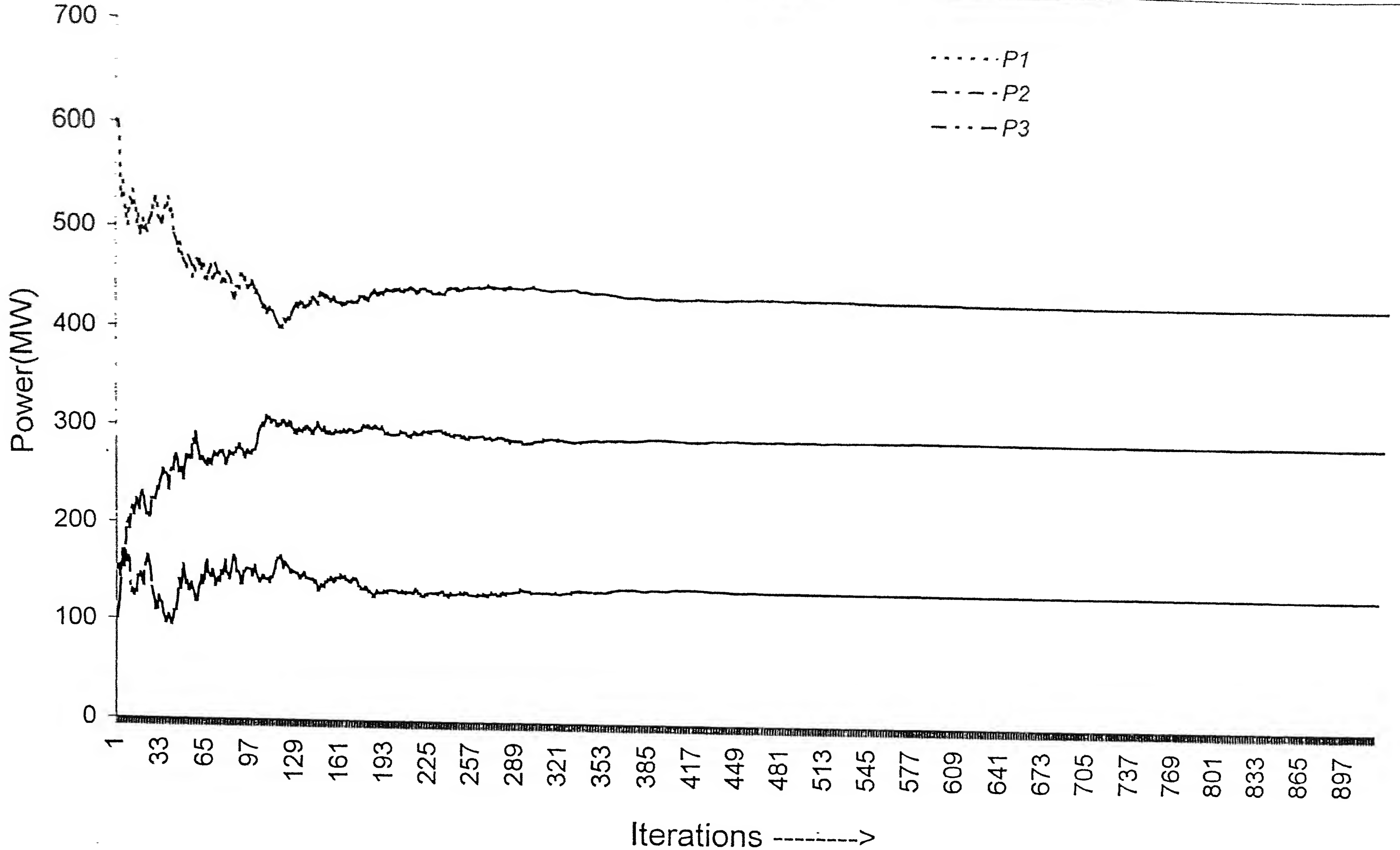


Fig.3.10.VARIATION OF POWERS FOR PROBLEM 3.4.1(CASE3) USING BEST COOLING SCHDULE

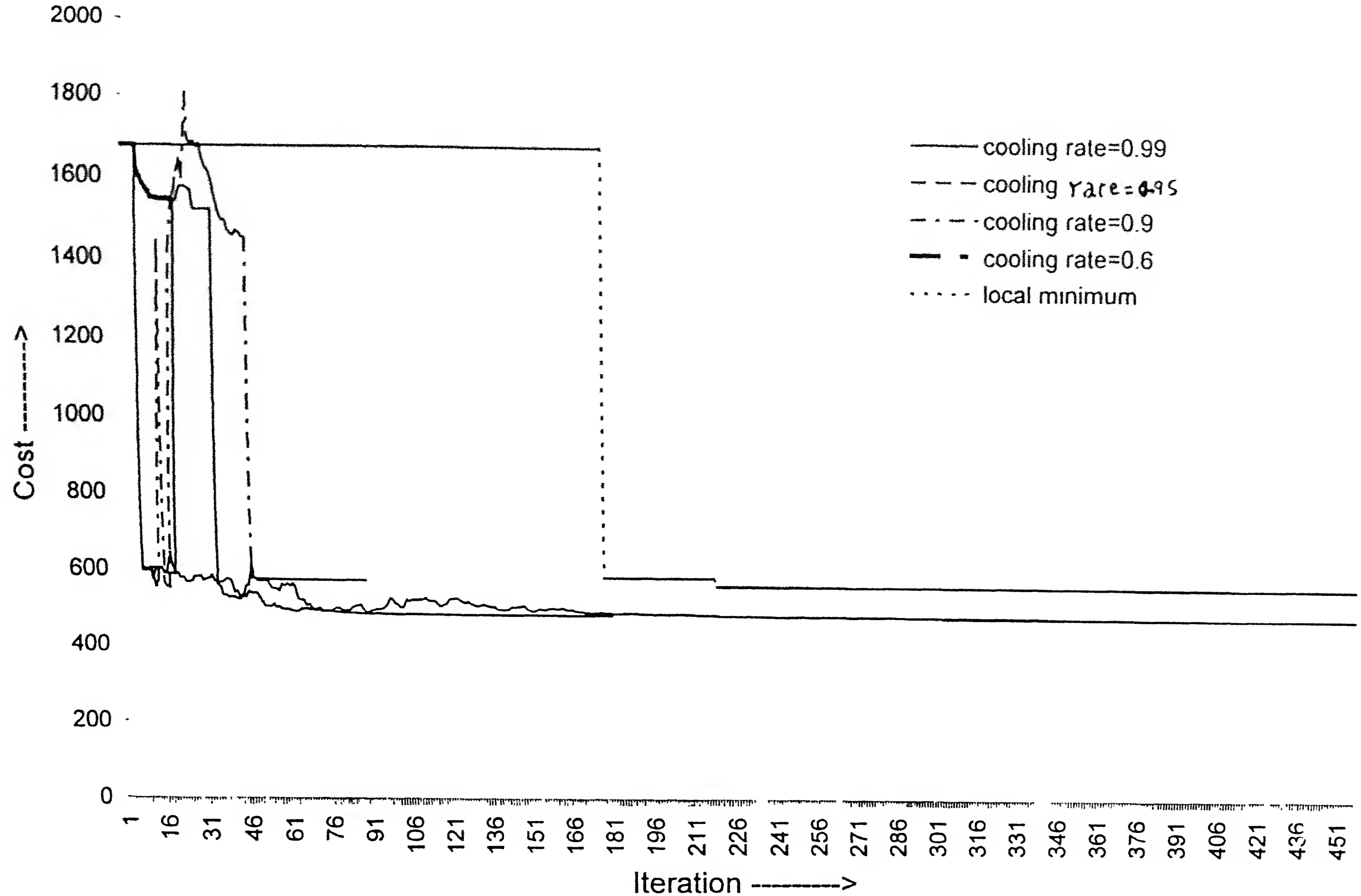


Fig.3.11.VARIATION OF COST FOR PROBLEM 3.4.2(CASE1) FOR DIFFERENT COOLING RATES

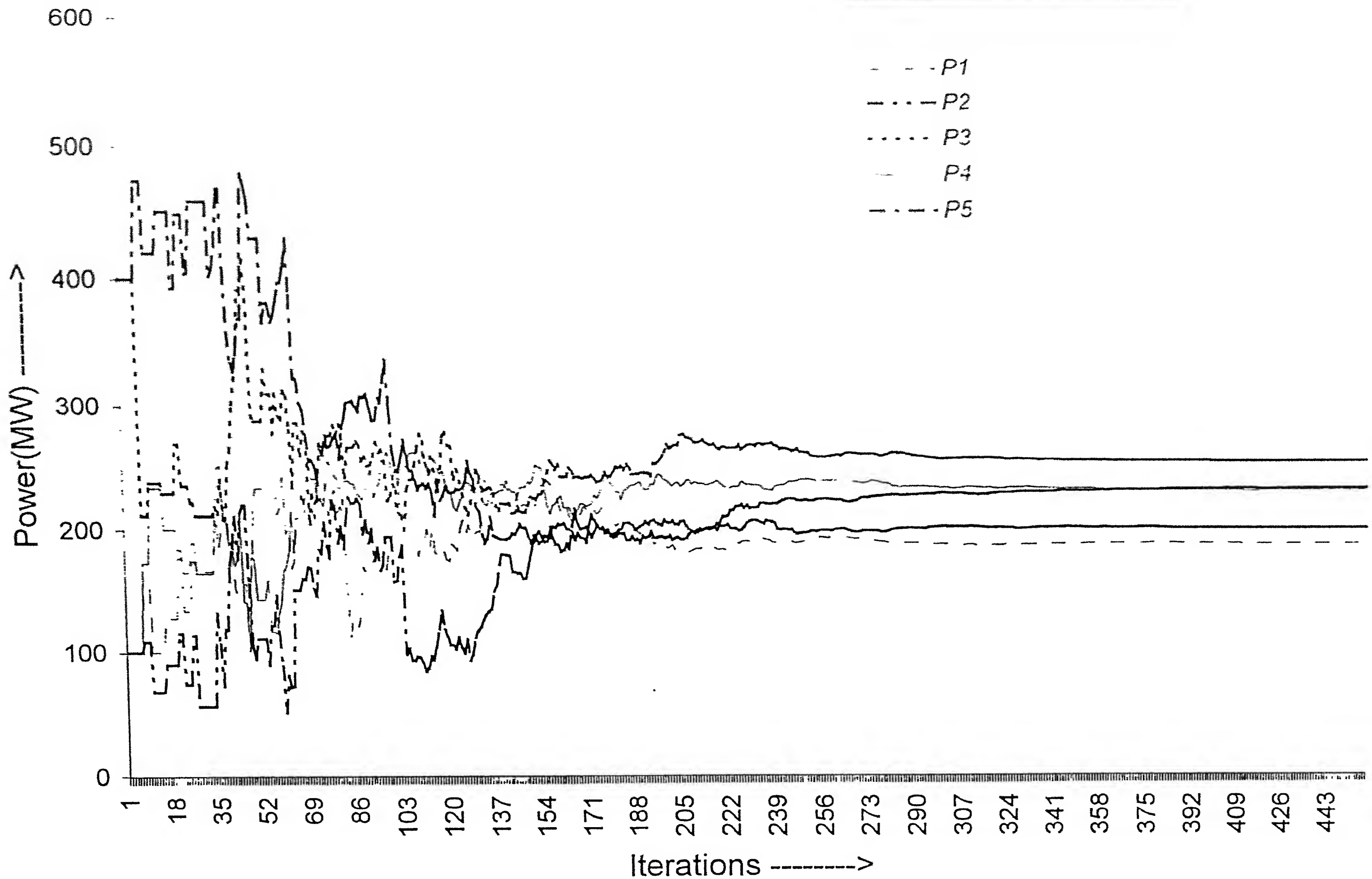


Fig.3.12.VARIATION OF POWERS OF PROBLEM 3.4.2(CASE1) FOR BEST COOLING SCHEDULE

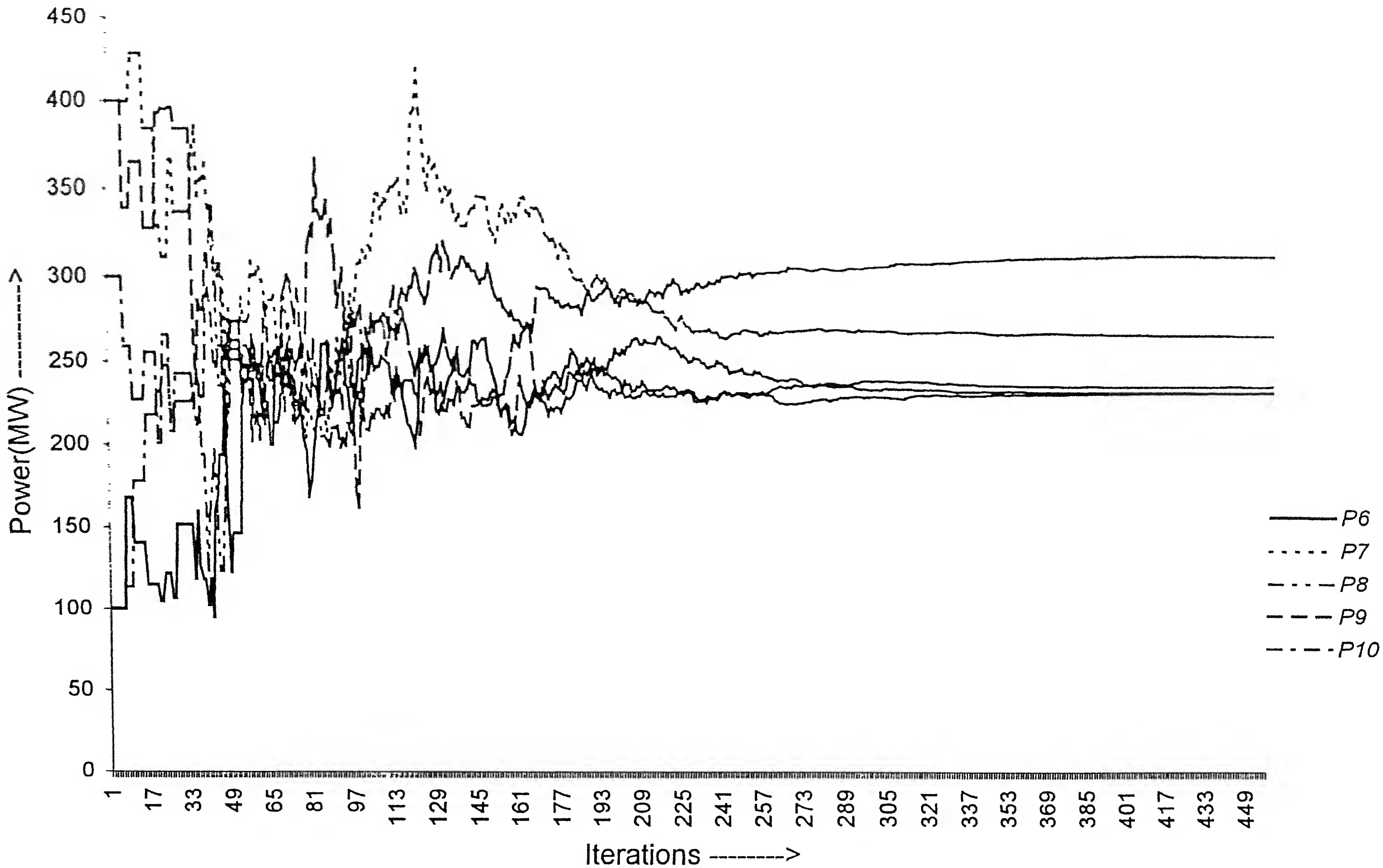


Fig.3.13.VARIATION OF POWERS FOR PROBLEM 3.4.2(CASE1) USING BEST COOLING SCHEDULE

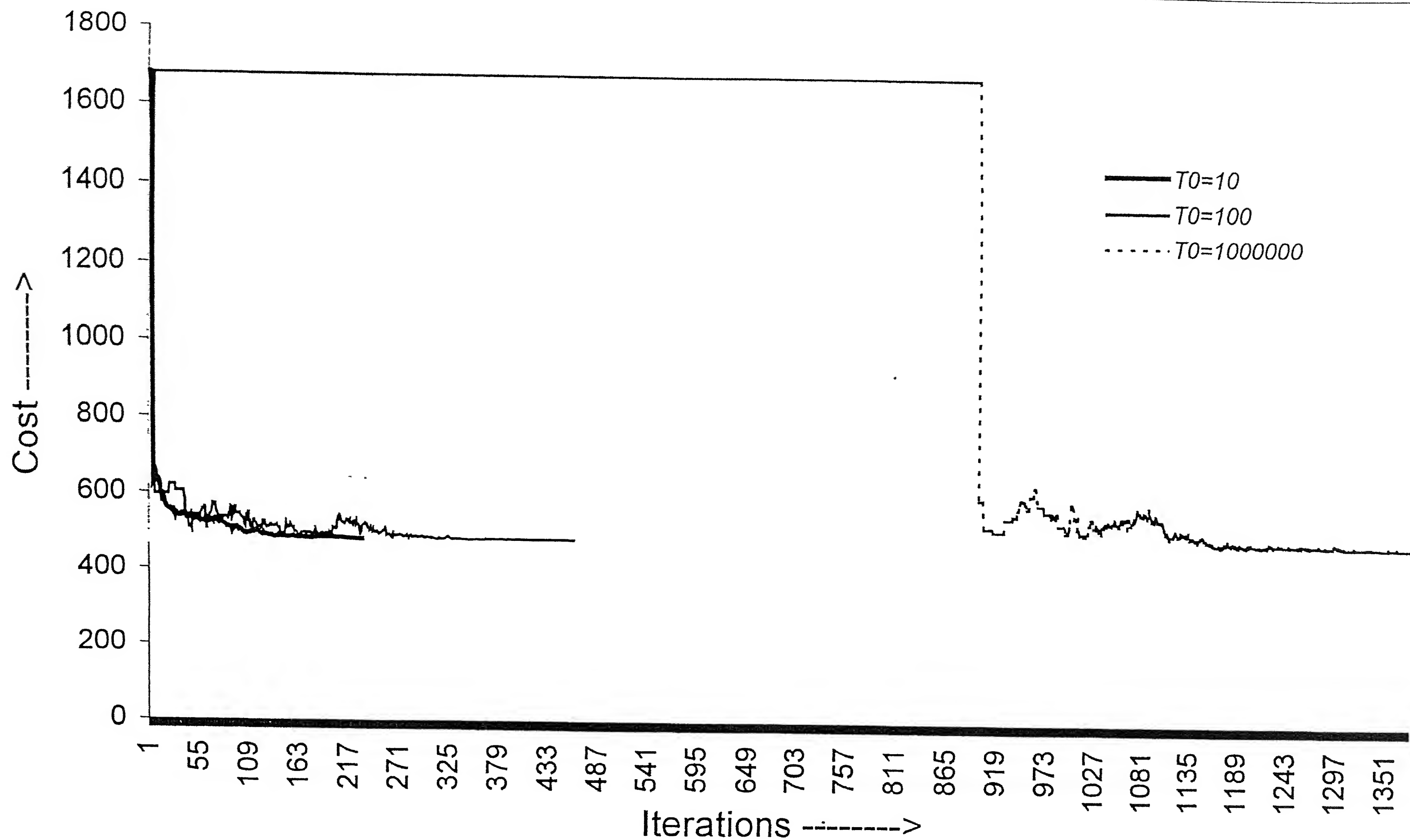


Fig.3.14.VARIATION OF COST FOR PROBLEM 3.4.2.(CASE1) FOR DIFFERENT INITIAL TEMPARATURES

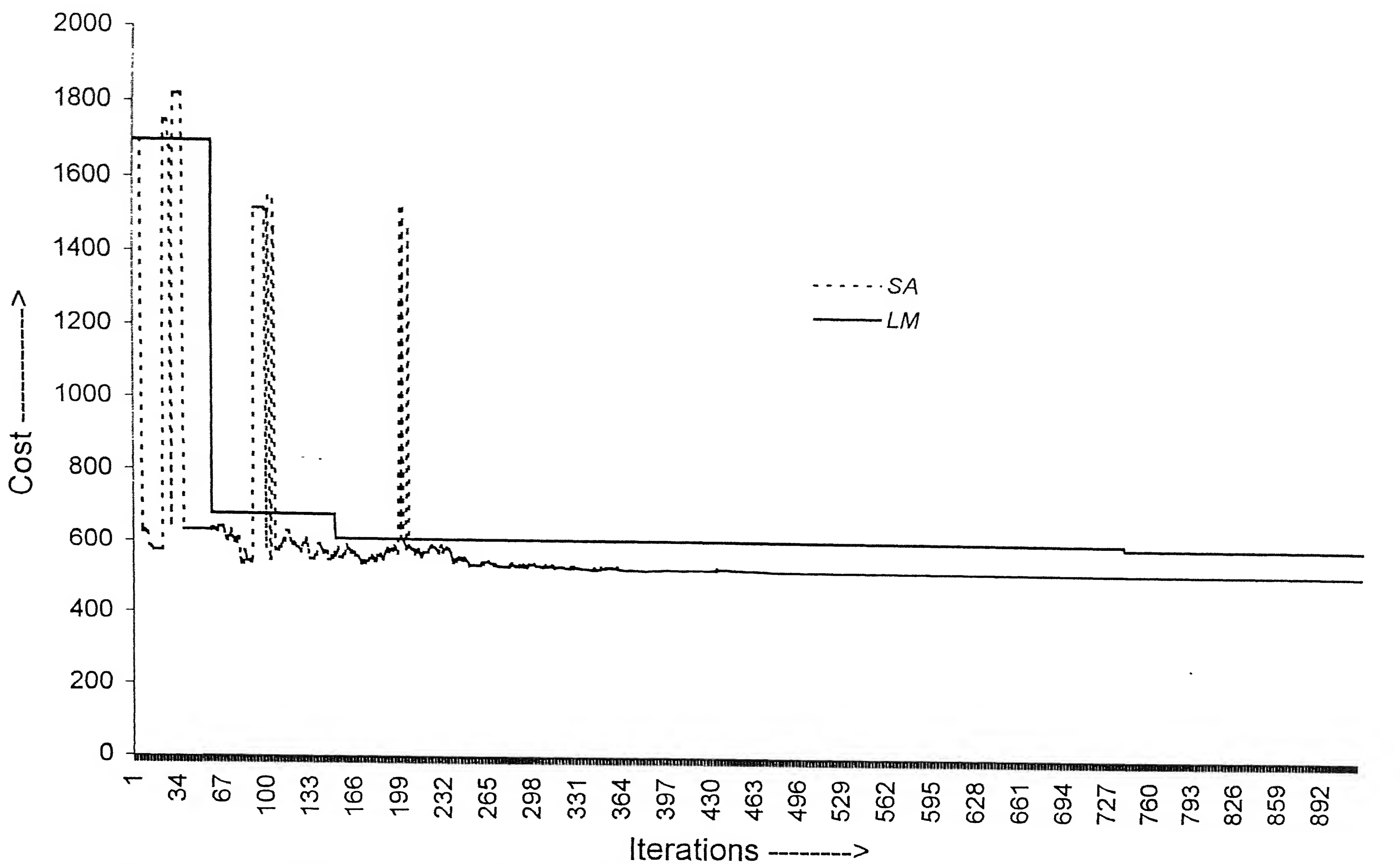


Fig.3.15.VARIATION OF COST FOR PROBLEM 3.4.2.(CASE2) WITH BEST COOLING SCHEDULE

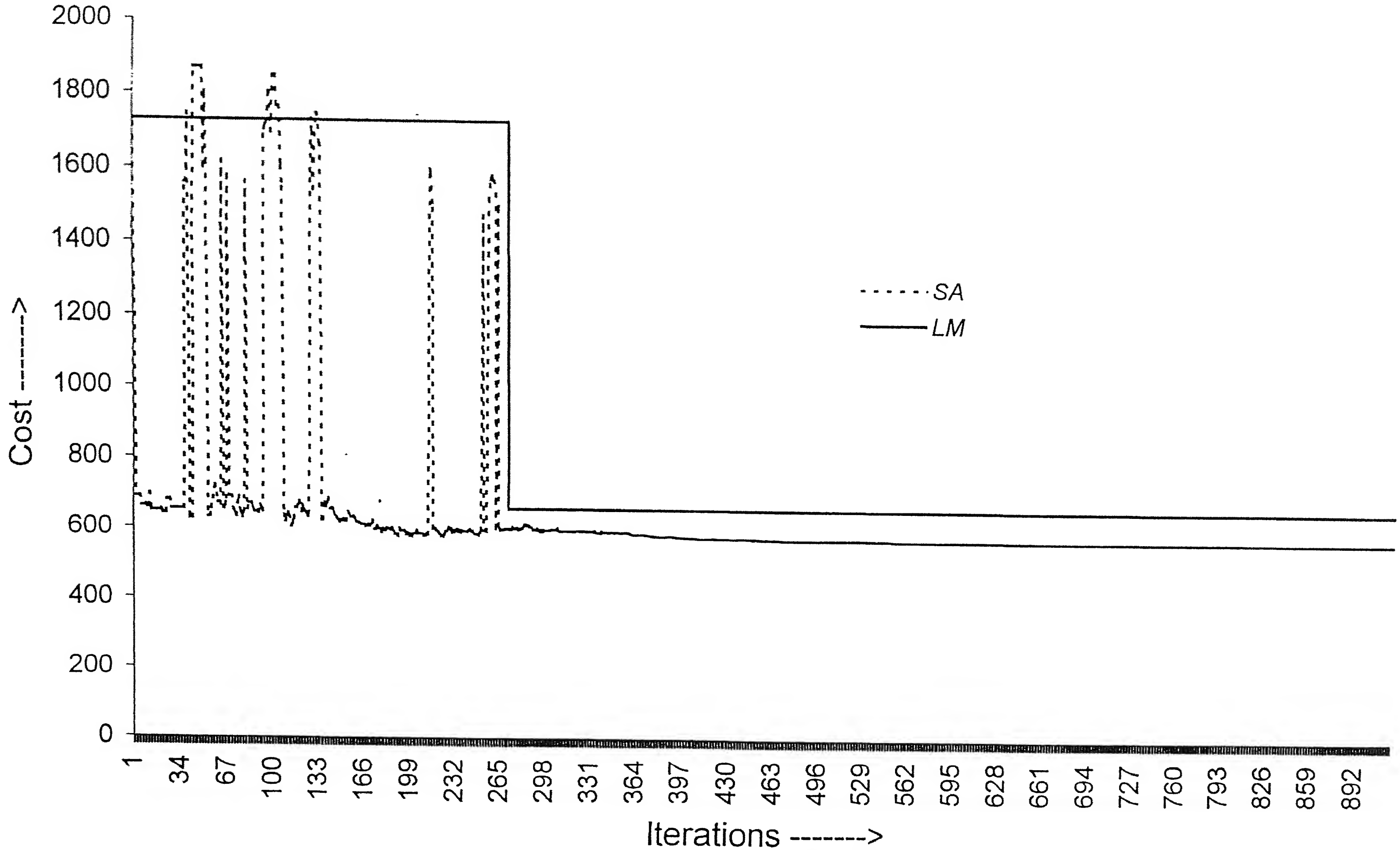


Fig.3.16.VARIATION OF COST FUNCTION FOR PROBLEM 3.4.2(CASE3) FOR BEST COOLING SCHEDULE

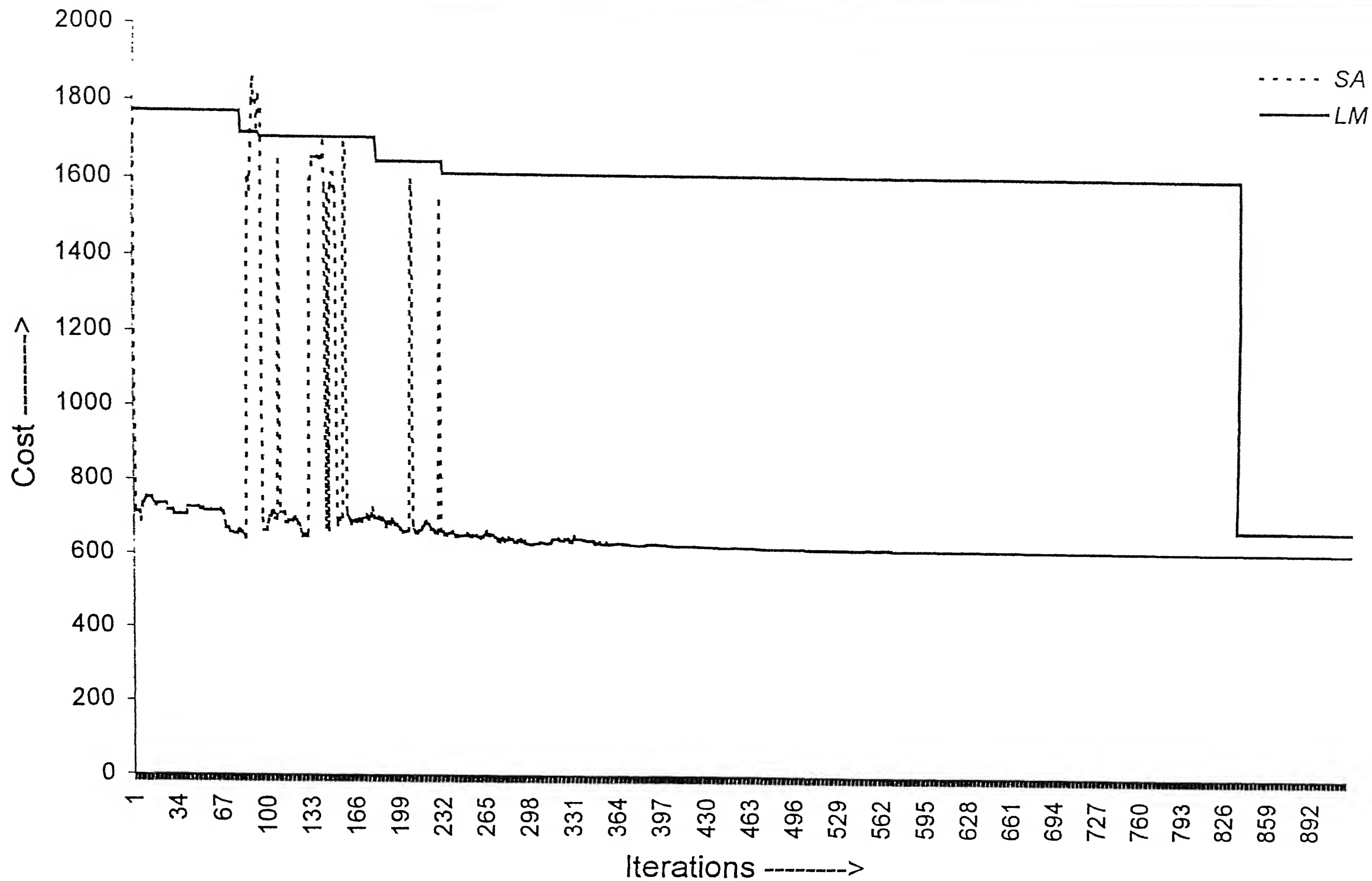


Fig.3.17.VARIATION OF COST FOR PROBLEM 3.4.2.(CASE4) FOR BEST COOLING SCHEDULE

Fig.3.18.VARIATION OF COST FOR PROBLEM 3.4.3.(STRATEGY 1) FOR ALL 6 HOURS USING BEST COOLING SYSTEM

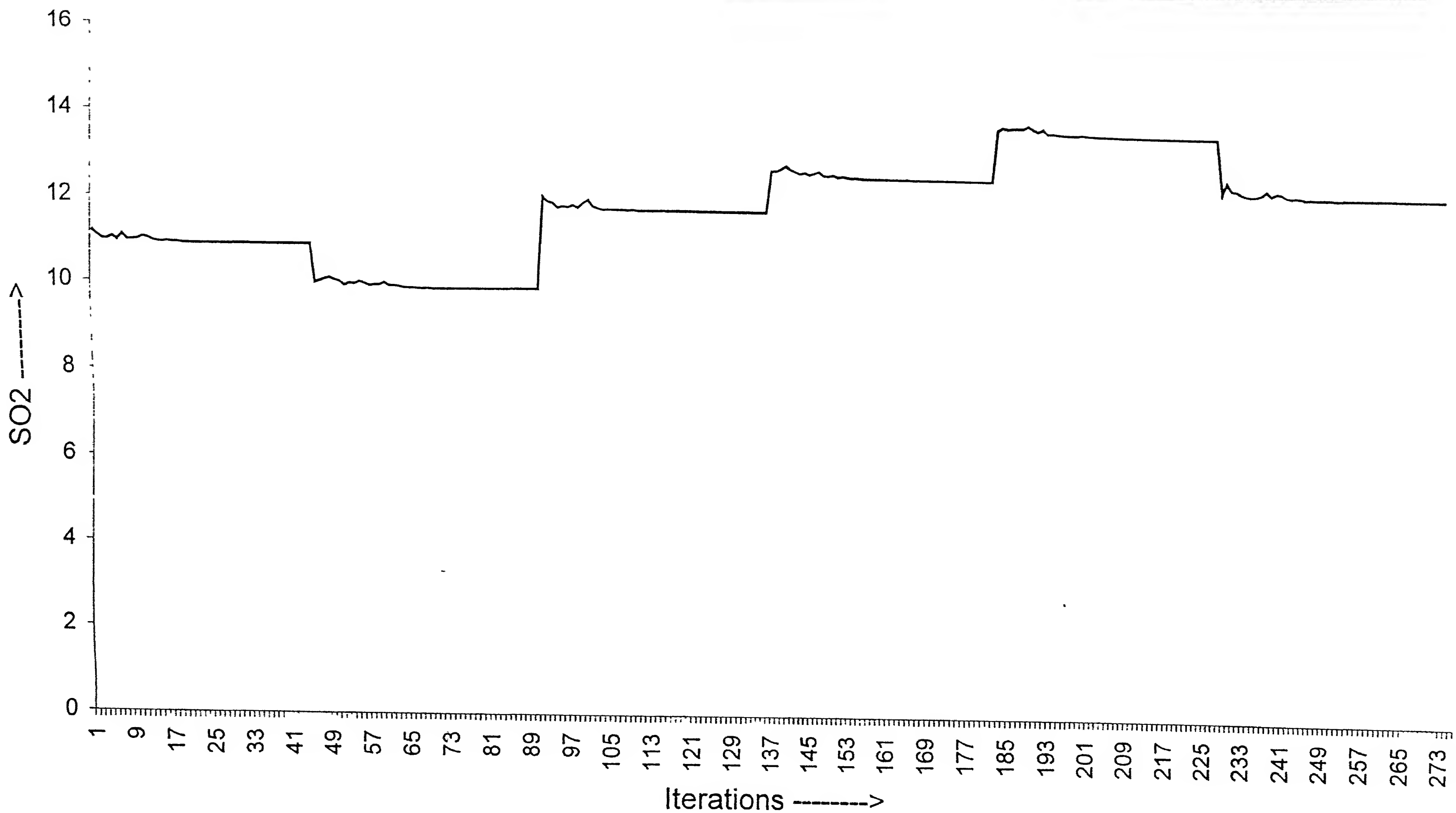


Fig.3.19.VARIATION OF COST(SO2) FOR PROBLEM 3.4.3.(STARTEGY 2) FOR ALL 6 HOURS USING BEST COOLING SCHEDULE

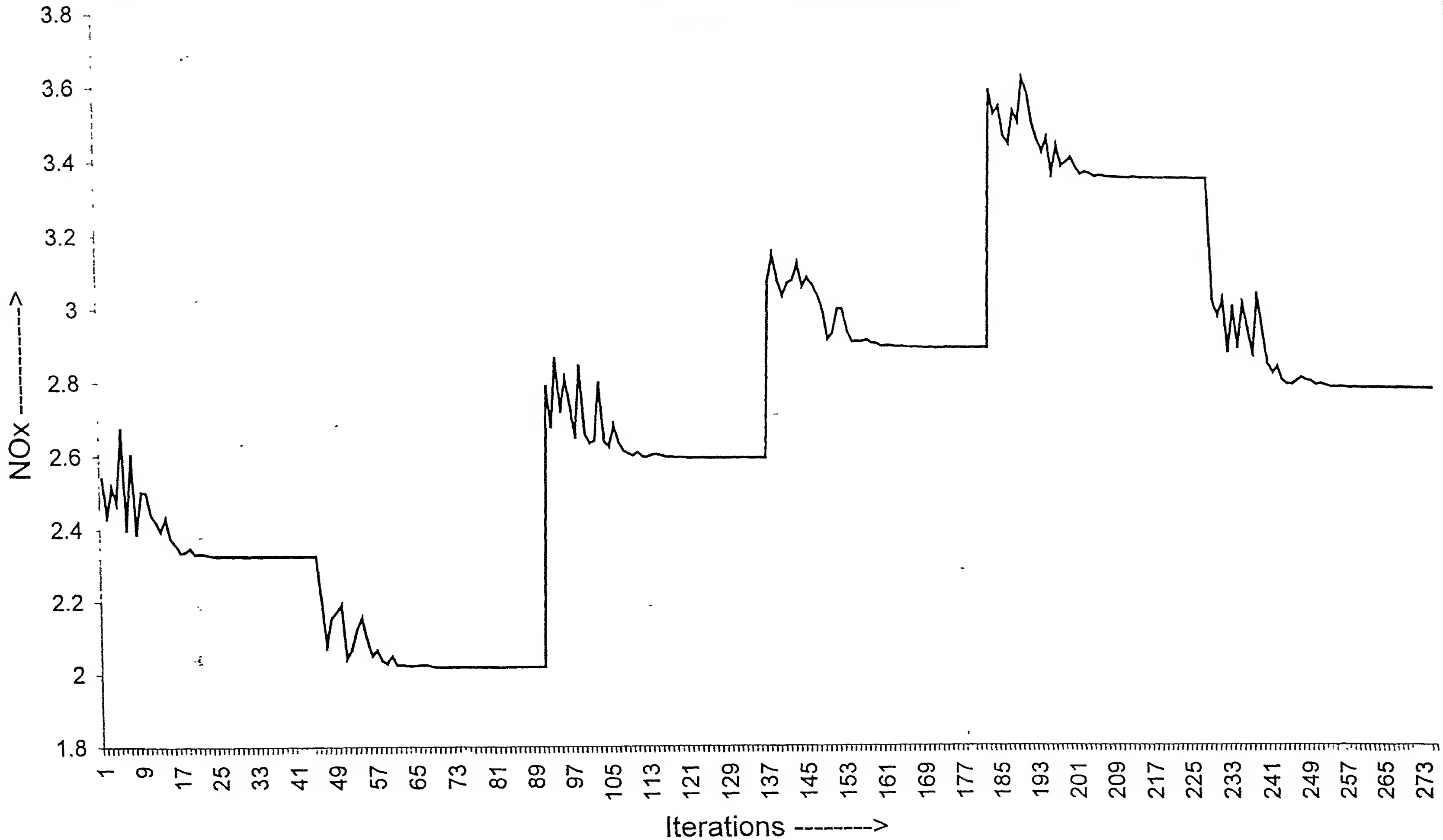


Fig.3.20.VARIATION OF COST(NOx) FOR PROBLEM 3.4.3.(STRATEGY 3) FOR ALL 6 HOURS USING BEST COOLING SCHEDULE

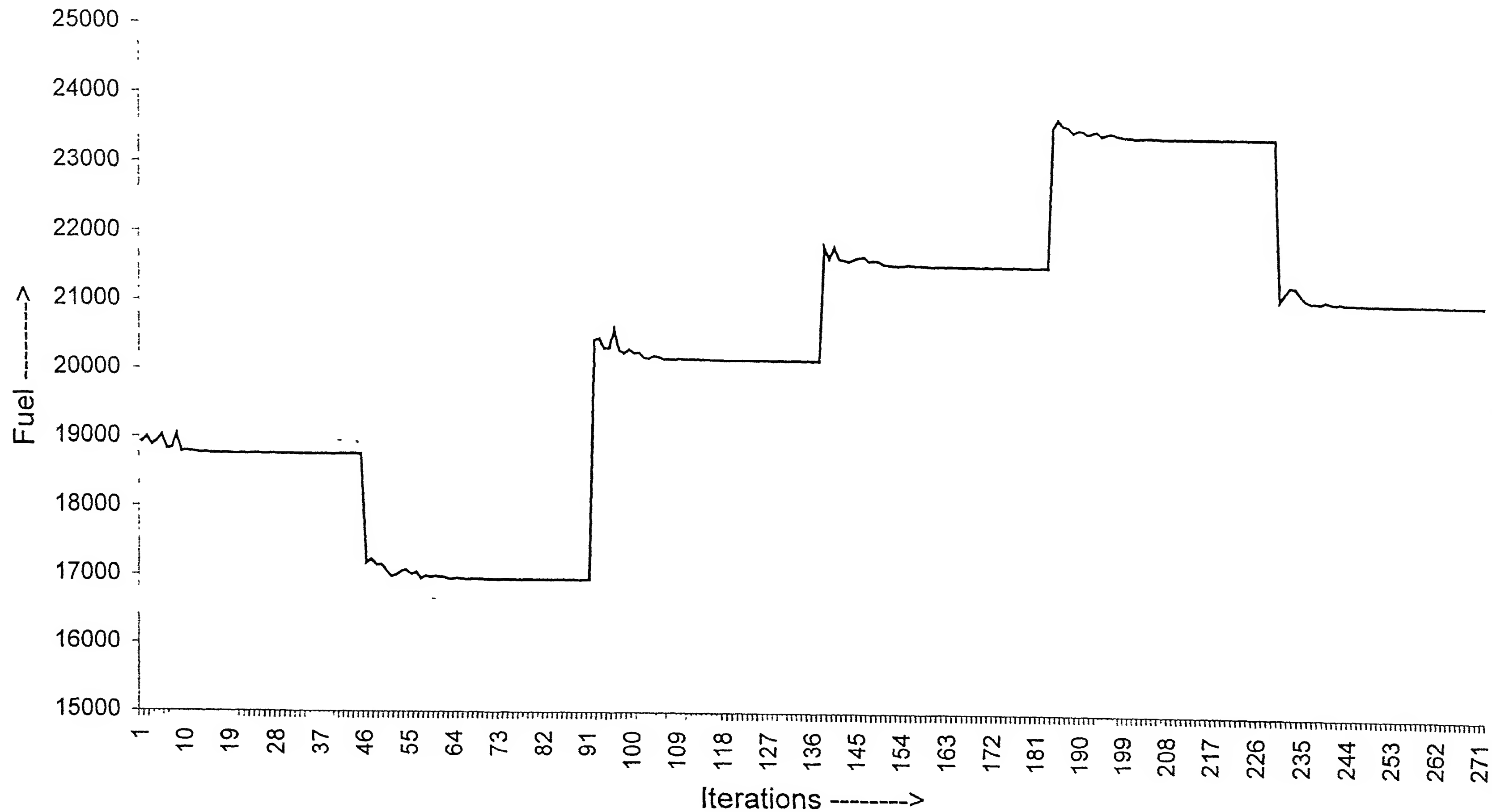


Fig.3.21.VARIATION OF COST(FUEL) FOR PROBLEM 3.4.3(STRATEGY 4) FOR ALL 6 HOURS USING BEST COOLING SCHEDULE

Fig.3.22.VARIATION OF COST FOR PROBLEM 3.4.3.(STRATEGY 5) FOR ALL 6 HOURS USING BEST COOLING SCHEDULES

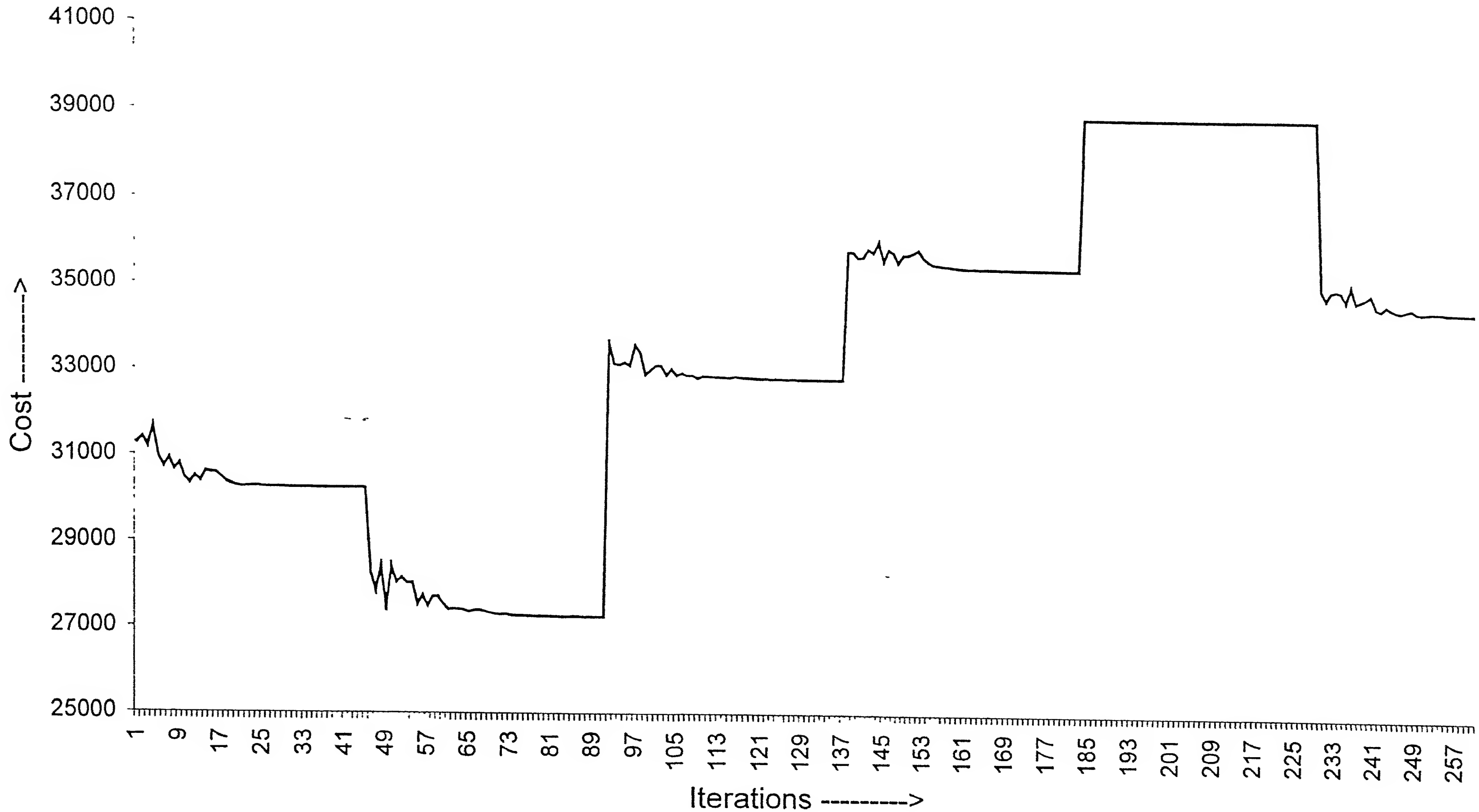


Fig.3.23.VARIATION OF COST FOR PROBLEM 3.4.3(STATEGY 6) FOR ALL 6 HOURS USING BEST COOLING SCHEDULE

Fig.3.24.VARIATION OF COST FOR PROBLEM 3.4.3.(STRATEGY 7) FOR ALL 6 HOURS USING BEST COOLING SCHEDULE

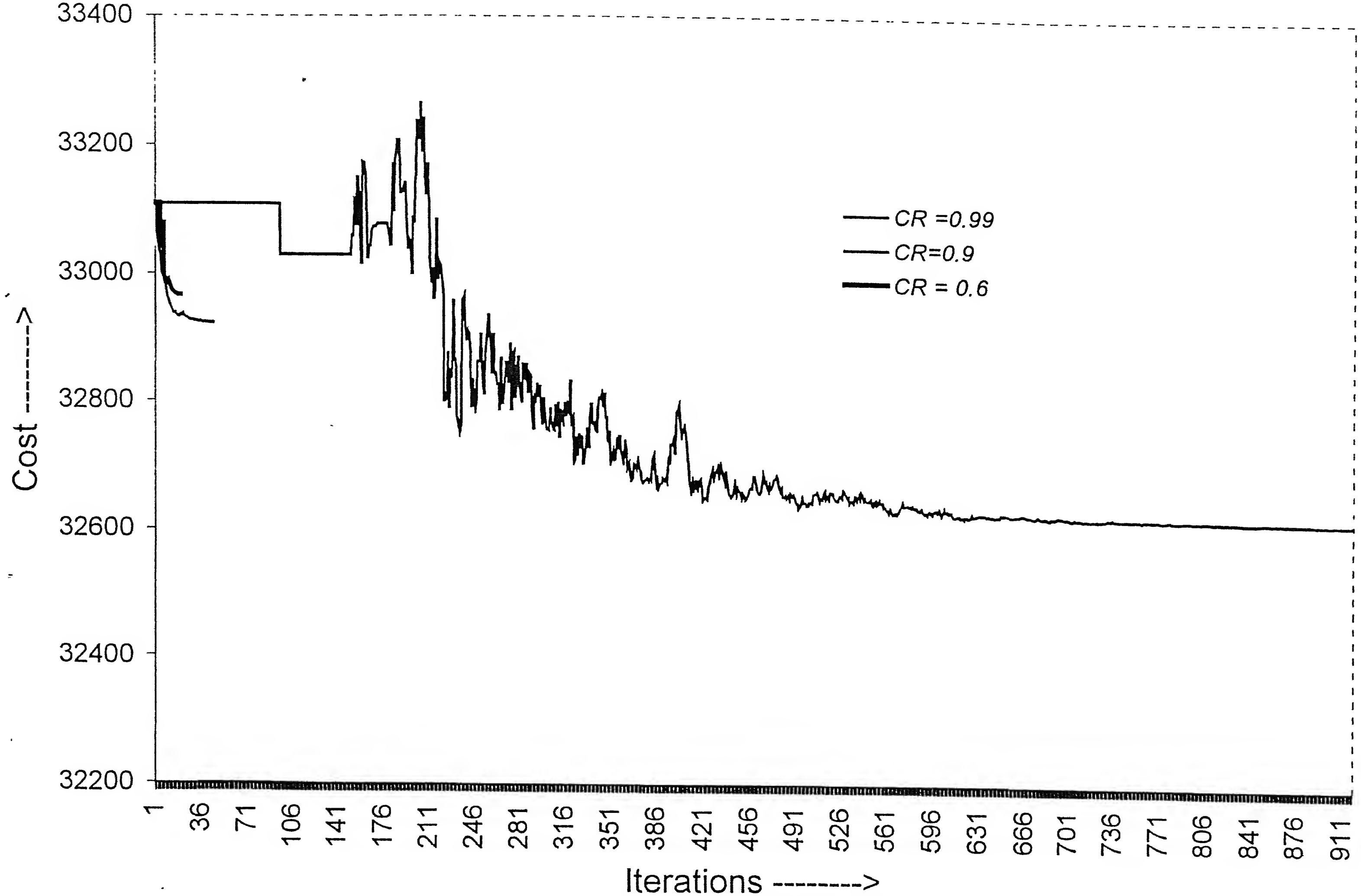


Fig.3.26.VARIATION OF COST FOR PROBLEM 3.4.4.(CASE1) FOR DIFFERNT COOLING RATES

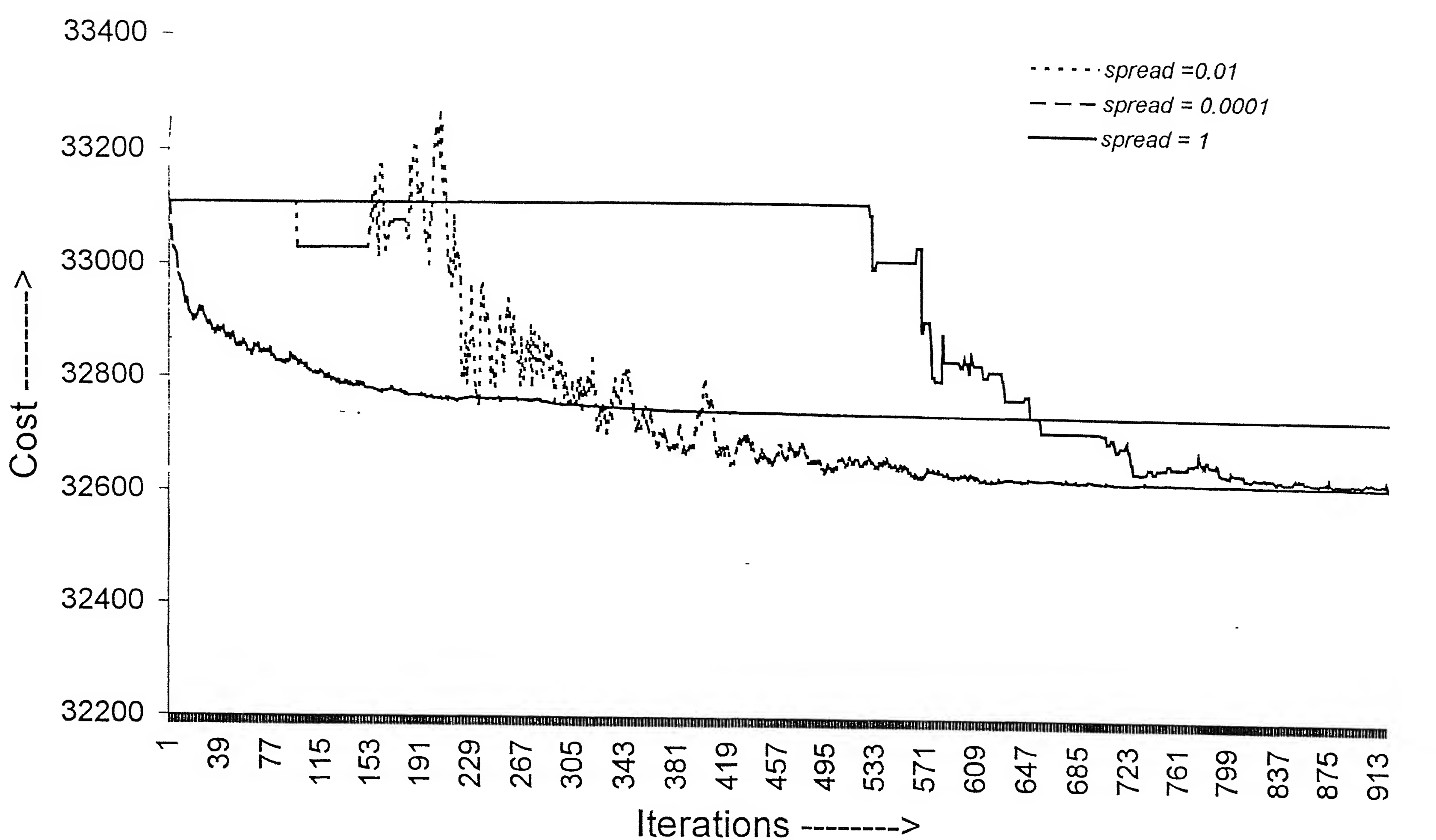


Fig.3.27.VARIATION OF COST FOR PROBLEM 3.4.4.(CASE1) FOR DIFFERENT SPREAD FACTORS

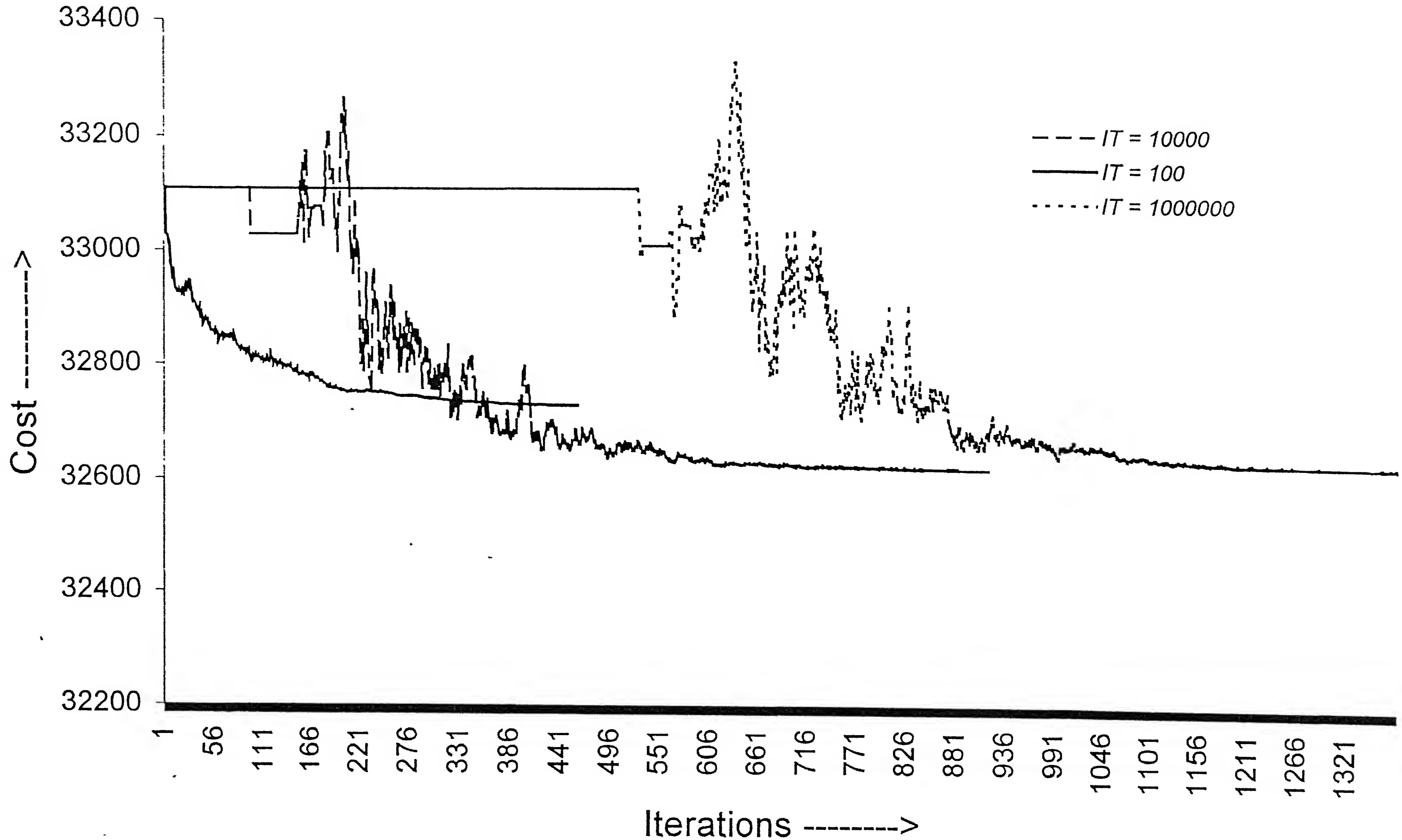


Fig.3.28.VARIATION OF COST FOR PROBLEM 3.4.4.(CASE1) FOR DIFFERENT INITIAL TEMPARATURES

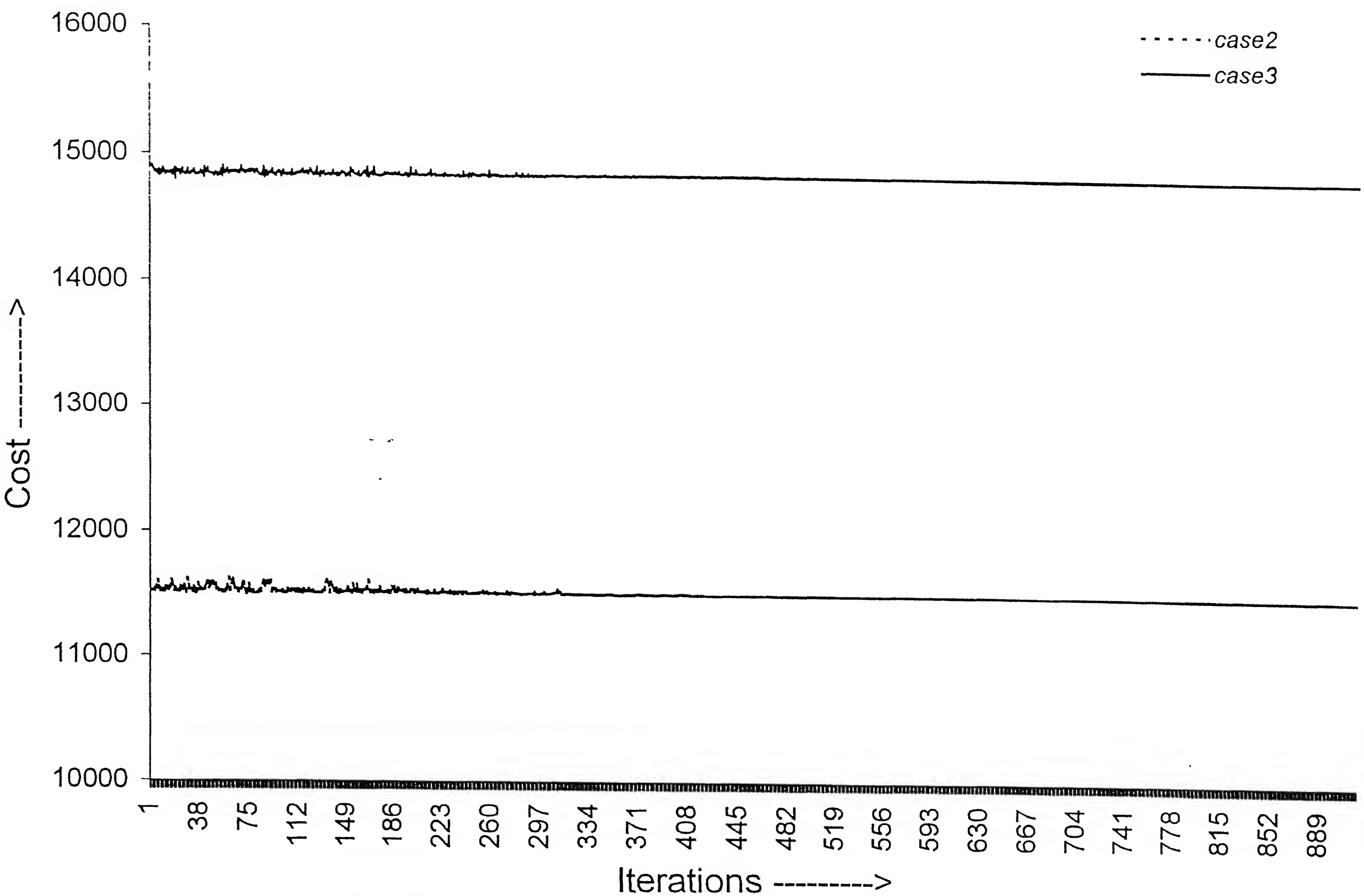


Fig.3.29.VARIATION OF COSTS FOR PROBLEM 3.4.4.(CASE 2 & 3) USING BEST COOLING SCHEDULE

Chapter 4

Simulated Annealing Applied to Hopfield Neural Networks

4.1. Introduction to Hopfield Neural Networks

Hopfield neural networks proposed by J.J.Hopfield in 1982 [13] are recurrent neural networks with symmetrical weight matrices in which the diagonal elements may or may not be zero. Hopfield in his paper described how an analysis of stable points could be performed for symmetrical recurrent networks. The analysis was based on the use of a Liapunov energy function for the nonlinear equations. The most interesting aspect of Hopfield networks is the characterisation of the state of the network with this energy function. Hopfield suggested the energy function of continuous-time, single-layer feedback networks, also called the gradient type networks as,

$$\mathbf{E}(\mathbf{v}) = -\frac{1}{2}\mathbf{v}^{t}\mathbf{W}\mathbf{v} - \mathbf{i}^{t}\mathbf{v} + \sum_{i=1}^{n}\mathbf{G}_{i}\int_{0}^{v_i} f_i^{-1}(z)dz \tag{4.1}$$

where E(**v**) is the energy function in the n-dimensional output space $\mathbf{v}^{\mathbf{n}}$. Matrix **W** represents the symmetrical weight matrix of the Hopfield network and $\mathbf{i}^{\mathbf{t}}$ represents the threshold of the neurons. Third term in the equation 4.1.represent the inverse of the non-linear activation function. Hopfield has shown that changes of **E** in time, will always be in the direction toward lower values of the energy function in $\mathbf{v}^{\mathbf{n}}$ space, and thus will eventually reach a stable state. Because there will be finite number of states, the network will finally reach to a local minimum. The state of the system at convergence determines the output pattern. The state of the system to which it will actually settle depends on the initial state of the network

and the weight matrix **W**. For a fixed **W**, from any initial state, the system evolves by moving down the surface of the energy function until a local minimum is reached.

It is because of this property of Hopfield Neural Network, it has been applied to various optimization problems such as travelling salesman problem [14],scheduling [14] etc. Hopfield Neural Network has its well demonstrated capability in these areas. It has also been applied in the areas of image processing and control [15].

In the field of power systems, Hopfield networks has been applied to optimal power flow and economic load dispatch problems [6,8]. When applied to economic load dispatch problem, Hopfield Networks can handle nonconvex cost functions. It does not require the calculation of incremental fuel costs and incremental losses, which are needed in conventional methods. This saves lot of computer memory when complex systems are under use. Also hardware implementation is possible with Hopfield Networks. Even though Hopfield Networks provide a local optimal solution, because of the above-mentioned advantages, it has a good application in the area of economic load dispatch problem.

4.2. Mapping of Economic Load Dispatch Problem into Hopfield Network

In order to solve economic load dispatch problem using Hopfield Networks, an augmented energy function has been defined, which combines both the objective function of the ELD (2.5) and the constraint equation (2.8) as,

$$\mathrm{E} = A(D + L - \sum_{i} \mathrm{P}_i)^2 / 2 + B \sum_{i} (a_i + b_i \mathrm{P}_i + c_i \mathrm{P}_i^2) / 2 \qquad (4.2)$$

where A(≥0) and B(≥0) are the weighting factors. The weight matrix and the threshold of the neurons for the Hopfield Network can be obtained by mapping the above energy function in (4.2) into Hopfield energy function in (4.1). Generally the third term in (4.1) will be very less and so it will be neglected during mapping. Thus by comparing both these energy functions, we can get,

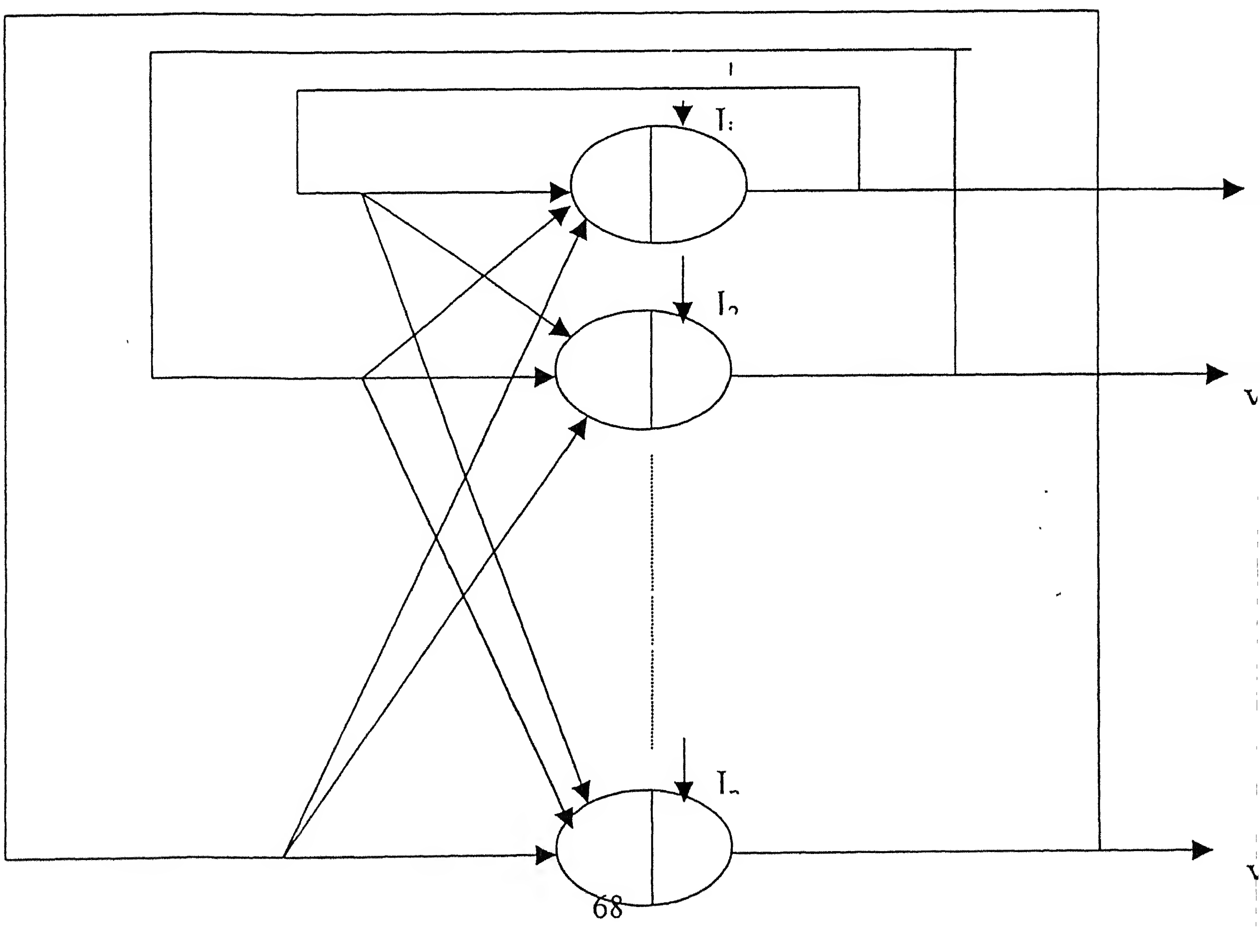
$$
\begin{aligned}
w_{ii} &= -A - Bc_i \\
w_{ij} &= -A \\
I_i &= A(D+L) - Bb_i/2
\end{aligned}
\tag{4.3}
$$

Thus the (4.2) itself takes care of the power balance constraint of the ELD problem, while minimising the cost function of ELD. To take care of the operating limits on generators, a modified sigmoidal function has been used for the neurons, so that the neuron outputs will remain in the specified limits. So the input-output relationship of each neuron, with this modified sigmoidal function is given by,

$$
v_i = g_i(u_i) = (\mathbf{P}\max_i - \mathbf{P}\min_i)/(1 + \exp(-u_i/U_0)) + \mathbf{P}\min_i \tag{4.4}
$$

where v_i is the output of i'th neuron and u_i is its net input. U_0 is a coefficient, which determines the shape of the sigmoidal function. The weights and the thresholds, which are obtained in (4.3), with v_i and u_i, will completely define the Hopfield network, which can be viewed as in Fig.4.10.

Fig.4.10 Hopfield Network



Once the complete network has been formed by mapping the ELD problem, the Hopfield iterative process can be applied to the network, to find the stable state to which it will converge. The differential synchronous transition model used in computation for this Hopfield neural network has been given in (4.4).

$$u_i(k) - u_i(k-1) = \sum_j w_{ij} v_j(k) + I_i \\ v_i(k+1) = g_i[u_i(k)]. \tag{4.5}$$

When the energy of the Hopfield network reaches a stable state after implementing the algorithm mentioned in (4.4.) for several iterations, the stable output state $\boldsymbol{v}$ represents the required optimal loadings on generators. If the system is a lossy system, we can calculate the losses, L using the loss formula in each iteration and it can used to modify (4.3).

4.3. Application of Simulated Annealing to Hopfield Neural Networks

Even though Hopfield Networks give a local optimum solution to the problem, because of its advantages mentioned in section 4.1 it has a good application in the area of economic load dispatch problem. So to make Hopfield Networks give global optimum results so as to use the benefits offered by them, in this section an attempt has been made to apply Simulated Annealing Algorithm to Hopfield Networks.

In the usual Hopfield network, the state to which the system finally settles depends on the initial state of the network and the weight matrix **W**. Each state to which the system settles, represents a local optimum solution one of them being the global optimum solution. So if we can choose a proper weight matrix, such that the Hopfield Network finally settles at this global optimum solution then we can provide best possible solution for the economic load dispatch problem. The weight matrix which we are getting in (4.3.) by mapping ELD problem into Hopfield Network may not be a proper one to make the solution reach global optimum. Because these weights obtained in (4.3.) are completely dependent on the weighting factors A and B, which have to be chosen by trial and error method. Much

work has been going on in the area of selection of these weighting factors [16]. So, to avoid these problems, instead of using the weights obtained in (4.3.), some random weights have been used and then the Simulated Annealing method discussed in Chapter 3 has been applied to the weights, so as to obtain proper weights which will give global optimum results when used by the Hopfield Network.

The algorithm, which has been discussed in section 3.2 of chapter 3, has now been applied on the weights of the network, instead of applying on the generator loadings. And with each weight matrix obtained in the simulated annealing loop, the Hopfield Algorithm has been run. Since we won't have any constraints on weights, it is difficult to judge, from what starting weights, the process has to be started and in which region, the weights have to be updated. But from (4.3.) it can be understood that, the weights are completely dependent on the weighting factors A and B and they are almost equal to –A, as B will be very less compared to A generally. So in the present work, for each problem that has been studied, best possible A and B values have been taken from [17] and the operating limits of the weights have been fixed as –c * A to +c * A. Where c is a constant which has been selected to give as much variation to weights as possible.

4.4. Simulation Results and Discussions

The discussed methodology has been applied on the problems, which are discussed in chapter 3 and the results have been presented below.

Since Hopfield Network energy function is quite sensitive for changes in weights, whenever the cooling schedule landed at improper weights, Hopfield Network has given undesired results. In this section, the results obtained from the Hopfiled Network, when the cooling schedule lead to proper weights have been presented. The variation of the generator loadings etc. due to Hopfield updating have been shown in graphs for each problem.

4.4.1. Three Generator Problem

The three different cases that are there in this problem and their system data have been discussed in chapter 3, section 3.4.1. To solve this problem using Hopfield Networks, the energy function given in (4.2.) has been used. The thresholds were calculated using (4.3.) and the weights of the Hopfield Network have been chosen randomly. The discussed Simulated Annealing procedure has been applied on the weights and the results obtained from the Hopfield Network have been presented below.

Table 4.1. Simulation Results of problem 4.4.1.for all the three cases.

	P_1	P_2	P_3	Total power[MW]	Total cost [$/h]
Case 1	395.8828	329.249	124.417	849.5488	8191.73
Case 2	598.8209	185.884	64.266	848.9709	7244.679
Case 3	429.6422	293.488	141.836	864.966 (loss = 15.6)	8338.498

4.4.2.System With Piecewise Quadratic Cost Functions

A brief explanation about this problem has been given in Chapter2 and Chapter 3,section 3.4.2. The cost function and the constraints for this problem will be given by (2.7), and the system data for this problem has been provided in Chapter3, section 3.4.2.

This problem also can be tackled, just as in problem 4.4.1. The only difference being, each time in the Hopfield iterative loop, we have to check the loading on each generator and we have to see, into which fuel region, that particular generator will fall according to its loading. And depending on the fuel region, in which the generator is operating the corresponding cost function has been used in energy calculations. So the Hopfield energy function in this case becomes,

$$E = A(D + L - \sum_{i=1}^{n} P_i)^2/2 + B\sum_{i=1}^{n}(a_{ij} + b_{ij}P_i + c_{ij} + P_i^2)$$

$$P_{i(min)} \leq P_i \leq P_{i(max)} \qquad (4.6.)$$

Where n is number of generators in the system and a_{ij} , b_{ij} and c_{ij} are the cost coefficients of i'th generator, when j'th fuel is under use.

The discussed Simulated Annealing procedure has been applied on the above system. The system has been tested for different loading conditions, 2400MW, 2500MW, 2600MW and 2700MW. The results obtained from the Hopfield Network, when best cooling schedule is used, have been presented in Table. 4.2.

Table. 4.2. Simulation results of problem 4.4.2.for all the loads.

S	U	2400MW		2500 MW		2600 MW		2700 MW	
		F	Gen.	F	Gen.	F	Gen.	F	Gen.
1	1	1	189.4798	2	206.1095	2	215.875	2	224.905
	2	1	202.22	1	206.3079	1	210.7318	1	215.1414
	3	1	253.8197	1	265.8326	1	278.821	1	292.304
	4	3	232.9938	3	235.896	3	239.0287	3	242.1523
2	5	1	241.4418	1	257.6237	1	275.0909	1	292.629
	6	3	232.994	3	235.8964	3	239.0298	3	242.156
	7	1	253.1695	1	268.8056	1	285.7755	1	303.005
3	8	3	232.9938	3	235.895	3	239.0287	3	242.152
	9	1	320.3858	1	331.478	1	343.4448	1	355.25
	10	1	239.43	1	254.9978	1	271.925	1	288.964
Total load		2398.93		2498.84		2598.75		2698.66	
Total cost		481.264		525.704		573.758		625.541	

4.4.3. System with Emission Dispatch Constraints

The detailed description about this problem and the various strategies which have been analysed under this problem have been presented in Chapter 3, section 3.4.3. The data of the test system used to implement this problem has also been given in section 3.4.3.

In this problem the cost functions of fuel, SO2 and NOx are of order three as described in (3.9). So the Hopfield energy function which has been discussed in section 4.1. and given by (4.1.) can not be applied for this problem as it is of second order. To tackle this problem, a third order energy function has been defined and the mapping of ELD into that third order function has been discussed in [18].

$$E(v)=-\frac{1}{3}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} w1_{ijk} v_i v_j v_k - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} v_j v_i - \sum_{i=1}^{n} i_i v_i + \sum_{i=1}^{n} \mathbf{G}_i \int_0^{v_i} f_i^{-1}(z)dz \qquad (4.7)$$

Where the weight matrix W1 has been used to map third order terms in the ELD problem. For this problem, the augmented objective function, which has to be minimised becomes

$$\mathbf{E} = A(Demand + L - \sum_{i=1}^{n} p_i)^2/2 + B\sum_{i=1}^{n} FP_i(a_i + b_i p_i + c_i p_i^2 + d_i p_i^3) +$$

$$C\sum_{i=1}^{n} Ea(sa_i + sb_i p_i + sc_i p_i^2 + sd_i p_i^3) + D\sum_{i=1}^{n}(na_i + nb_i p_i + nc_i p_i^2 + nd_i p_i^3) \qquad (4.8)$$

and the weights and the thresholds that are obtained after mapping (4.8) into (4.7) becomes,

$$w_{ii} = -A - B*FP_i*c_i - C*EA*sc_i - D*nc_i$$

$$w_{ij} = -A$$

$$w1_{ijk} = \begin{cases} -B*FP_i*d_i - C*EA*sd_i - D*nd_i & i=j=k \\ 0 & i \neq j \neq k \end{cases}$$

$$I_i = A(Demand + L) - B*FP_i*b_i/2.0 - C*EA*sb_i/2.0 - D*nb_i/2.0 \qquad (4.9)$$

So the above discussed method has been applied to this problem and the various strategies that have been discussed in Chapter 3, section 3.4.3. have been tested. The simulation results have been presented in Table 4.3. for all the strategies.

Table 4.3. Simulation results for Problem 4.4.3. for all the strategies.

Strategy	SO_2 limit (tons)	NO_x limit (tons)	Fuel (MBTU)	Cost ($)	SO_2 (tons)	NOx (tons)
Min Cost			121863	200709	71.442	16.62
Min SO2			121906	200954	71.432	16.67
Min Nox			122244	201562	71.627	16.615
Min Fuel			121167	201314	71.603	16.66
Min Cost with SO2 Limits	71.437		121957	200814	71.432	16.67
Min Cost with NOx Limits		16.618	121955	200807	71.432	16.62
Min cost + emission allow with SO2 limits	71.437		122124	201164	71.432	16.635
Min cost with SO2 and NOx limits	71.437	16.618	122544	201653	71.432	16.62

4.4.4. System with Prohibited Zones

The detailed description about this problem has been given Chapter 2 and Chapter 3, section 3.4.4. While solving the economic load dispatch problem, these prohibited zones will actually impose additional parametric inequality constraints on the generator loadings. Hopfield method of solving ELD problems, discussed in section 4.2. as such can not handle these parametric inequality constraints. Several methods have been used [8] to solve "economic load dispatch problem with prohibited zones " using Hopfield Networks. These methods generally first run the Hopfiled Network without considering the prohibited zones and then apply some strategy to make sure that the generator loadings are out of prohibited zones. Here the strategy that has been applied to tackle this problem has been described in the fallowing steps.

Step 1: First, apply the Hopfield dynamic transition model to determine the optimal generation for all the dispatchable units without considering prohibited zones.

Step 2: If no unit falls in the prohibited zone, then optimal generations are obtained and Step1 is the solution. Otherwise go to Step 3

Step 3:

a) Find the incremental costs of all the generators. λ^{min} and λ^{max} are the minimum and the maximum incremental costs of the generators, which fall in prohibited zones.

b) Check which generators are in prohibited zones. For each generator that is in prohibited zone, find the average power of the prohibited zone and if the generator loading is less than this average power, then force the generator loading to touch the lower limit of the prohibited zone. Otherwise force it to touch the higher limit.

c) Calculate the total power difference,ΔP before and after performing Step 3.(a). i.e. ΔP = total power before step.3.(a) – total power after step.3.(a). If this ΔP is less than 0, then reduce the loadings on generators (which are not in prohibited zones) which have incremental costs higher than λ^{max} in the ratio of their incremental costs. If this ΔP is greater than 0, then increase the loadings on the generators (which are not in the prohibited zones) which have incremental costs less than λ^{min}

d) Run step.3.(c) until no generator is in prohibited zone. If there are no generators which can meet the criteria in step3.(c) then redispatch on the remaining generators in the ratio of their incremental costs.

Step 4: Termination the computation.

The discussed algorithm has been applied on the problem which has been discussed in chapter 3, section 3.4.4.(case1). The data for the problem has also been presented in section 3.4.4. The basic energy function that is used by the Hopfield Network will remain same as in (4.2.). The simulation results obtained from this 15 unit test system has been presented in Table.4.4.

Table 4.4. Simulation results for problem 4.4.4.

Unit	Powers without taking prohibited zones into account(MW)	Powers taking prohibited zones into account(MW)
1	454.9998	450.434
2	454.9962	450.4308
3	130	130
4	130	130
5	316.74	335
6	459.998	455.433
7	465.00	460.4346
8	60.00	60
9	25.00	25
10	20	20
11	20	20
12	57.208	57.208
13	25	25
14	15	15
15	15	15
Total load	2648.94	2648.94
Total coat	32581.3	32585.1

In this problem, applying Hopfield method without considering the prohibited zones, driven unit 5 into prohibited zone. After applying the algorithm discussed in 4.4.4., to bring out the generators from prohibited zones, unit 5 has been forced to touch its higher level of the prohibited zone. Then redispatch has been carried out as per the algorithm, which has increased the cost slightly, but brought all the generators out of prohibited zones.

Conclusions

From the various results it can be observed that the application of Simulated Annealing to update the weights of Hopfield Network, do lead the Hopfield Network to give results which are comparable with that of the one got in chapter3. But in this case there is still some mismatch of power remained which can't be avoided in the case of Hopfield Networks, as this mismatch depends on the selection weighting factors of the cost function.

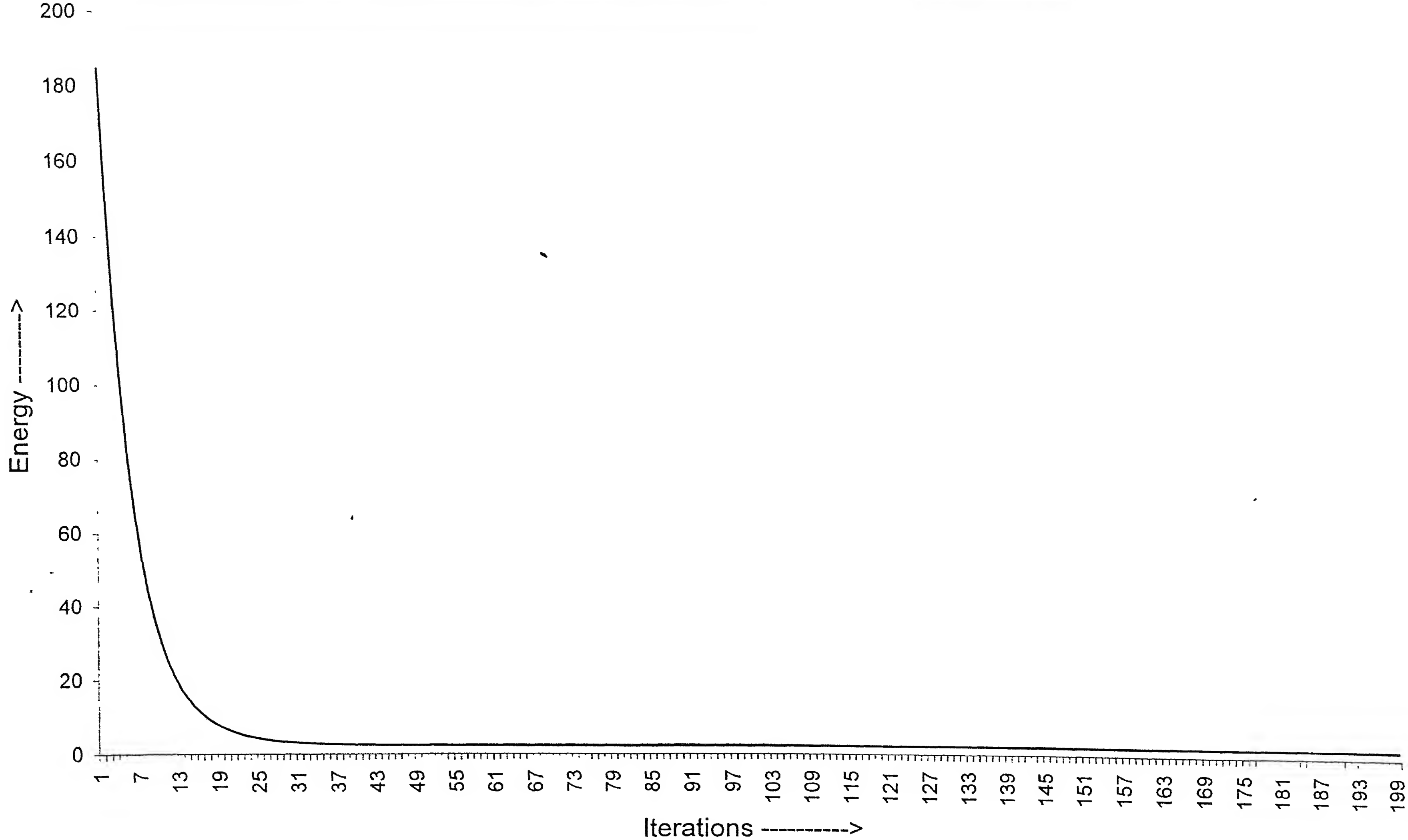


Fig.4.1.VARIATION OF HOPFIELD ENERGY

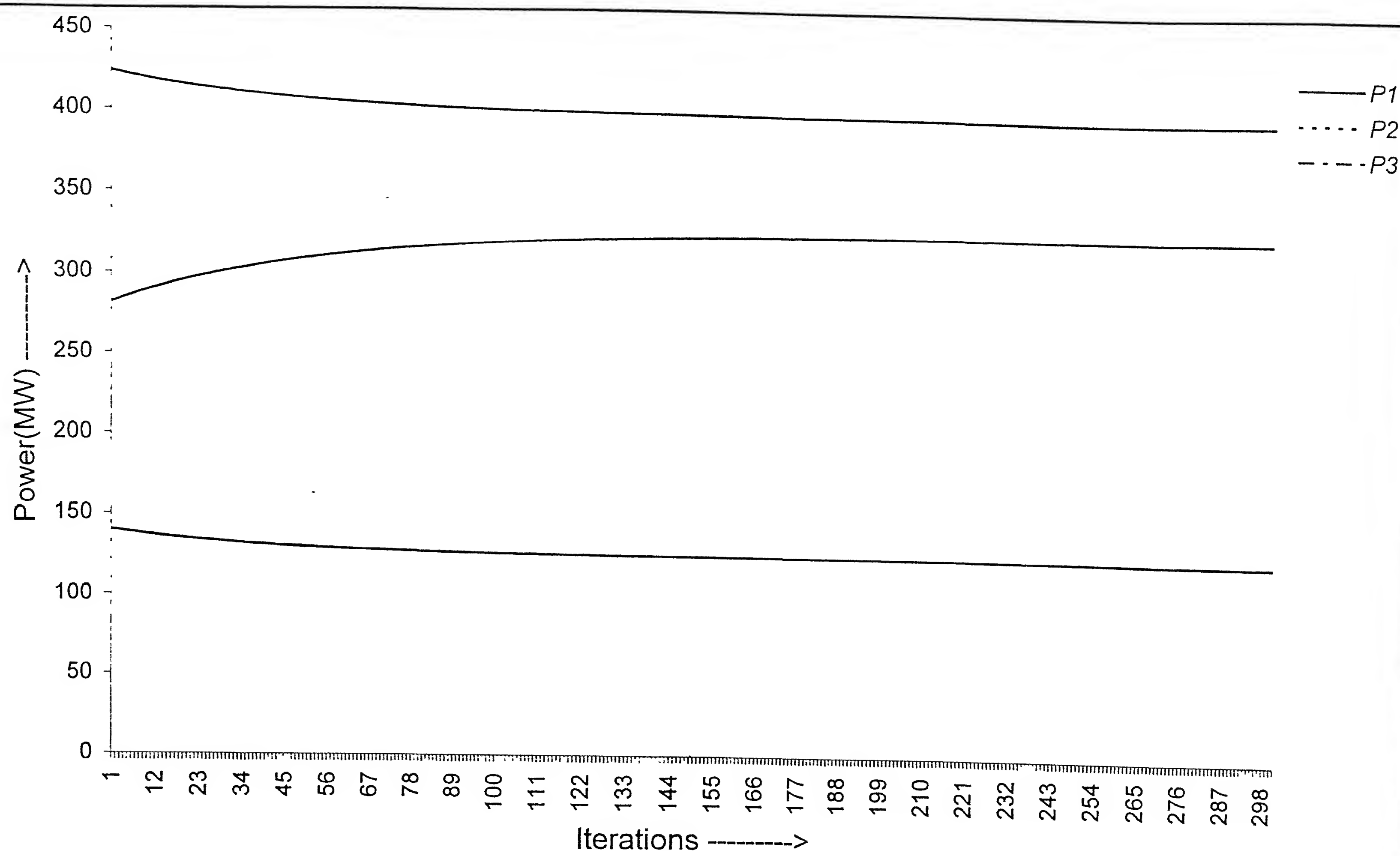


Fig.4.2.VARIATION OF POWERS FOR PROBLEM 4.4.1.(CASE1) USING HOPFIELD UPDATION

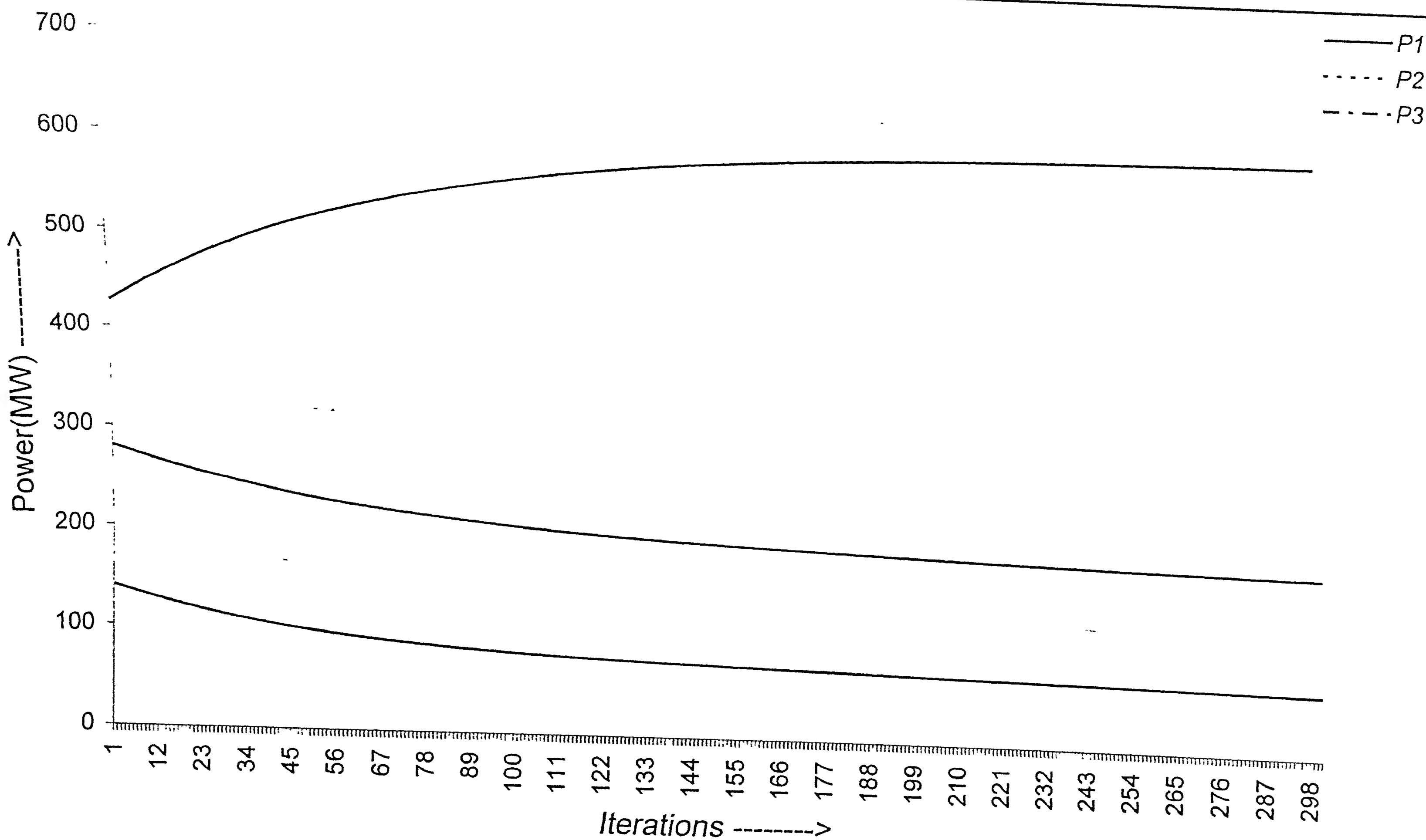


Fig.4.3.VARIATION OF POWERS FOR PROBLEM 4.4.1.(CASE2) DUE TO HOPFIELD UPDATION

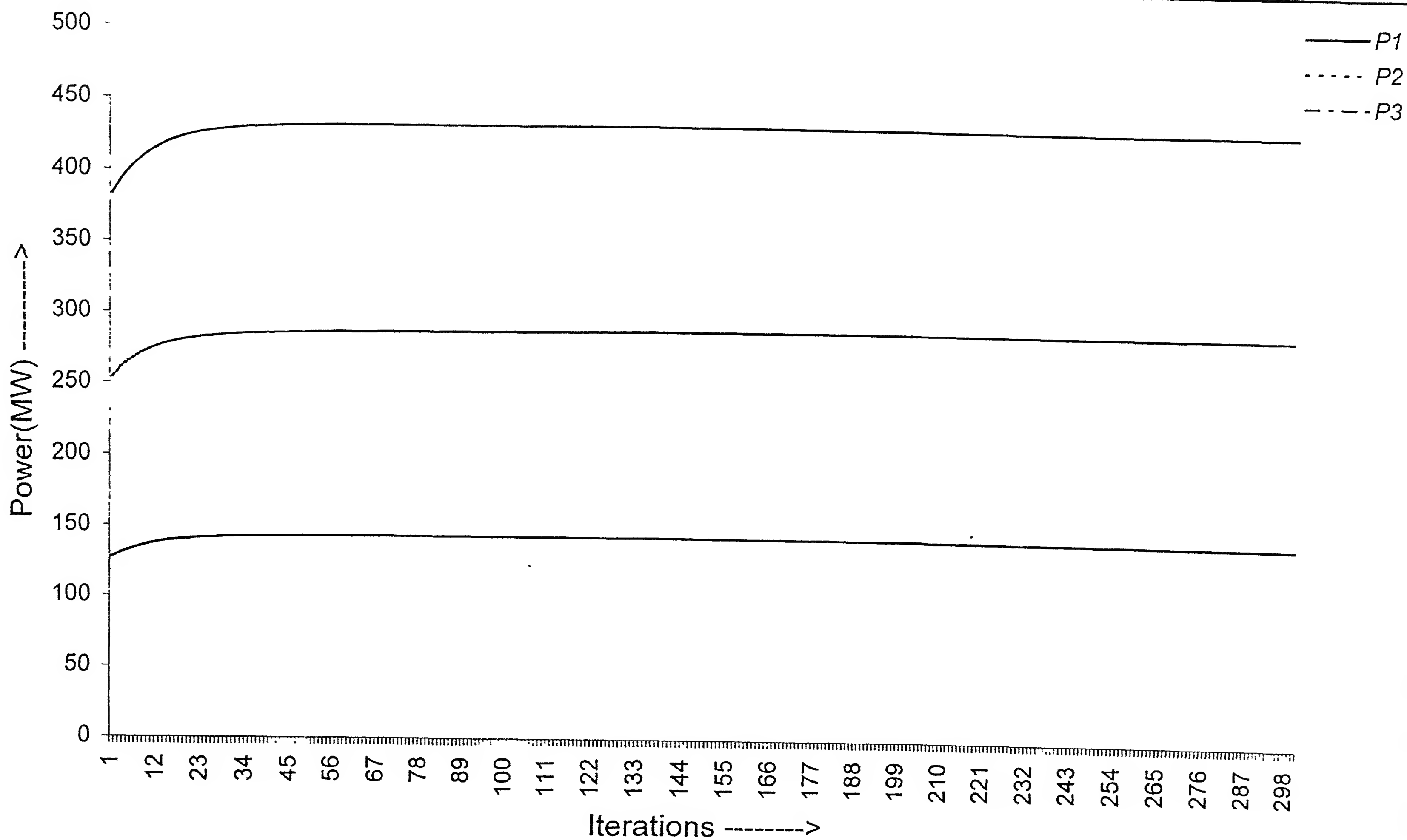


Fig.4.4.VARIATION OF POWERS FOR PROBLEM 4.4.1.(CASE 3) DUE TO HOPFIELD UPDATION

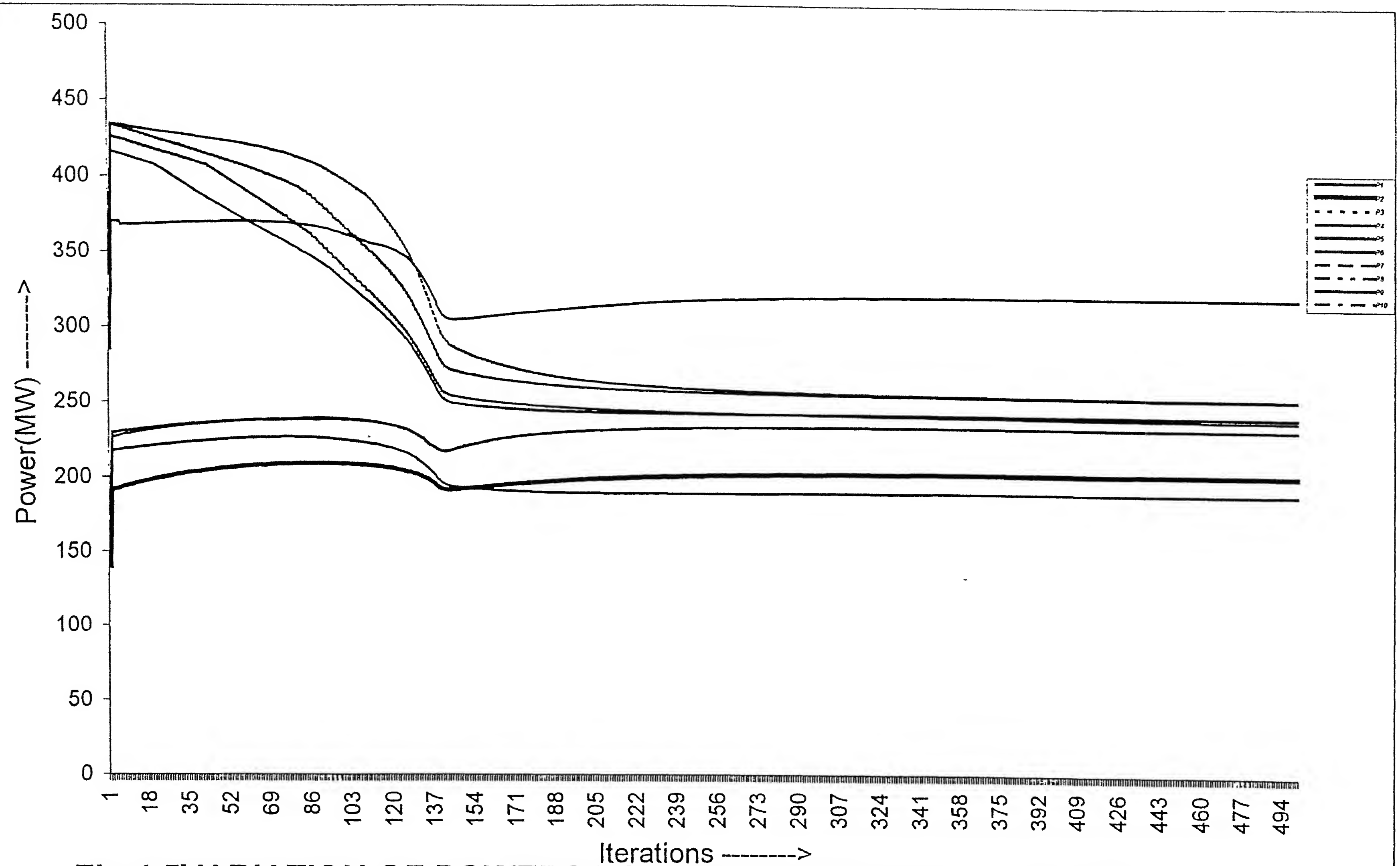


Fig.4.5VARIATION OF POWERS FOR PROBLEM 4.4.2.(case1) DUE TO HOPFIELD UPDATION

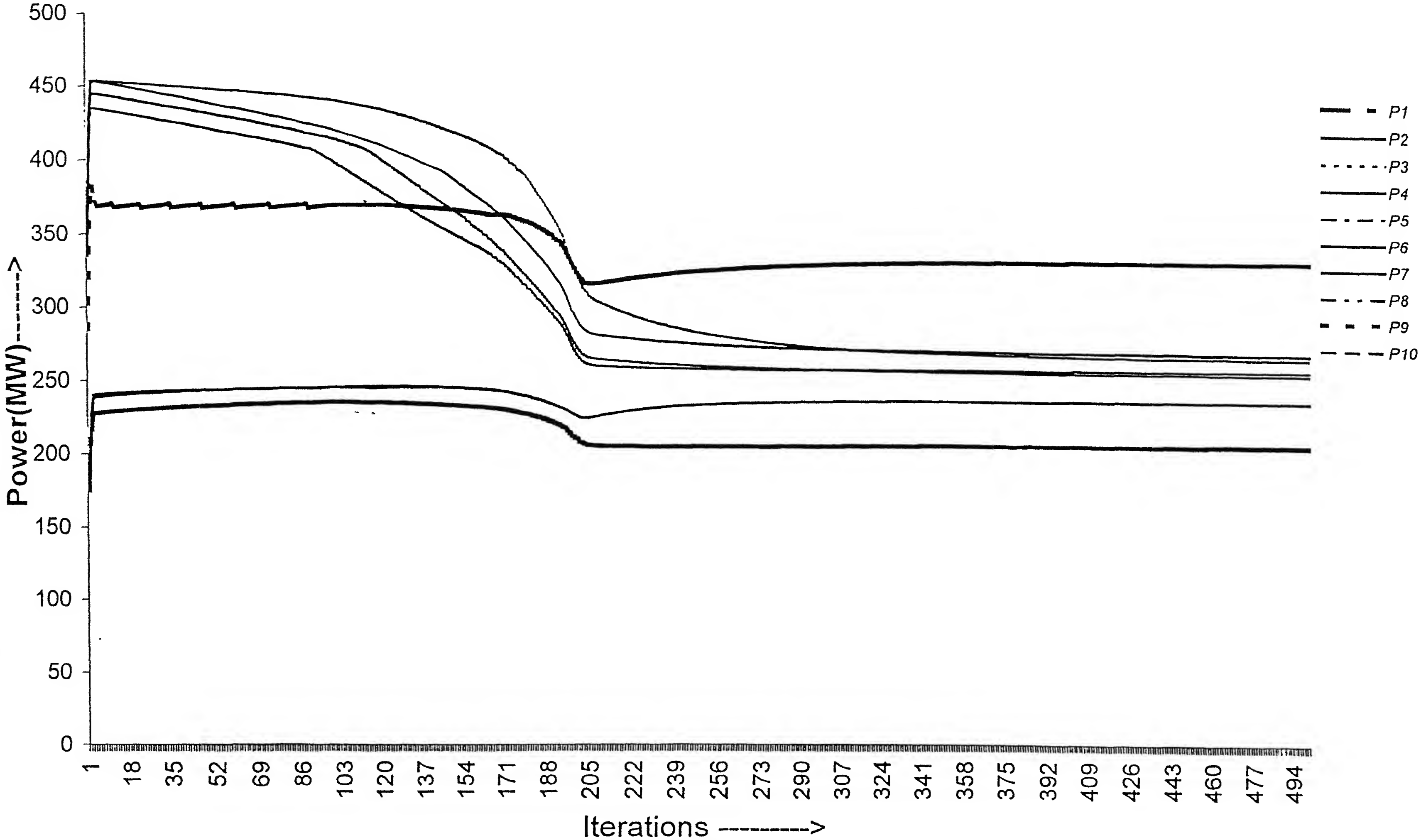


Fig.4.6.VARIATION OF POWERS FOR PROBLEM 4.4.2.(CASE 2) DUE TO HOPFIELD UPDATION

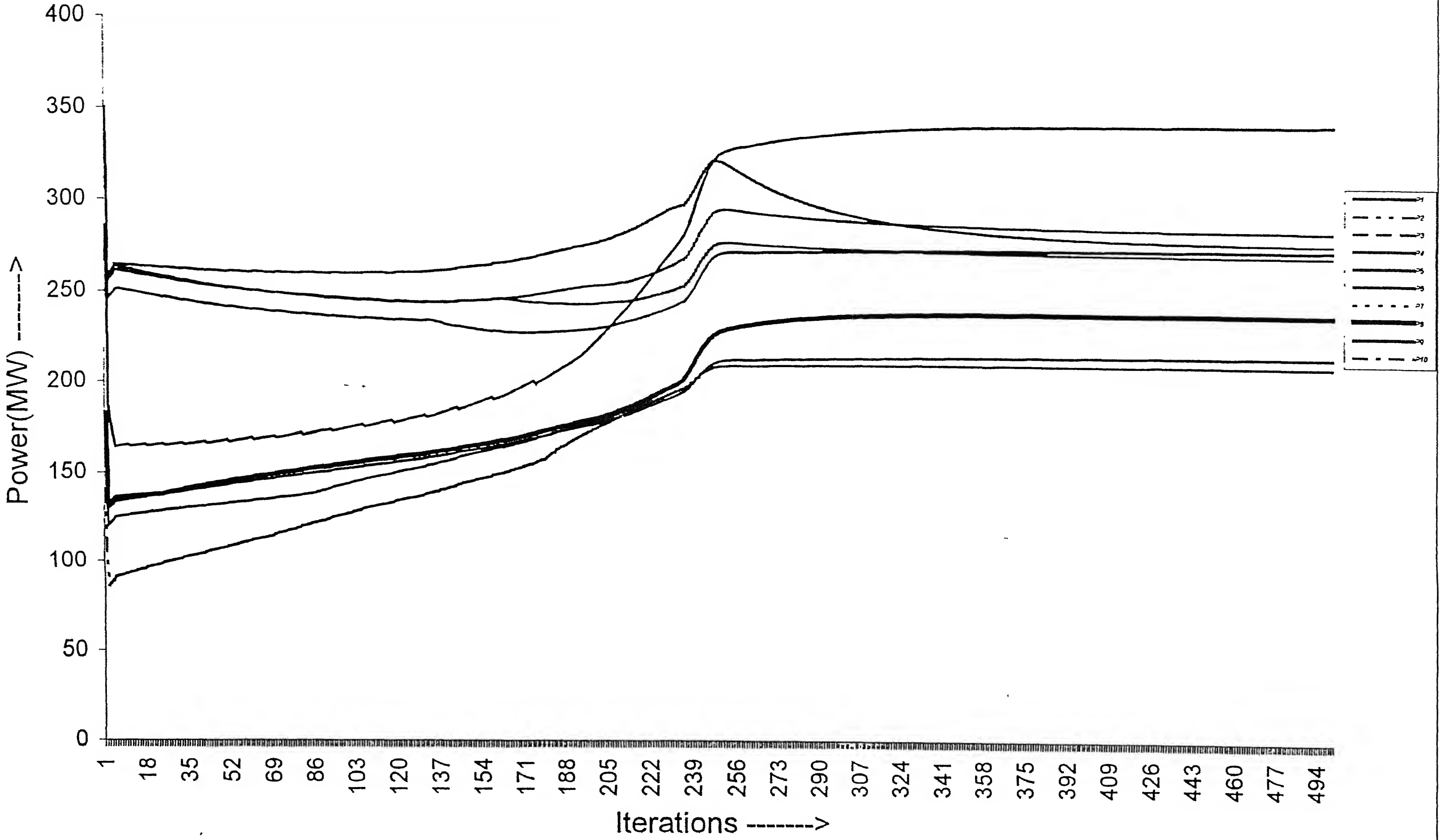


Fig.4.7.VARIATION OF POWERS FOR PROBLEM 4.4.2(CASE 3) DUE TO HOPFIELD UPDATION

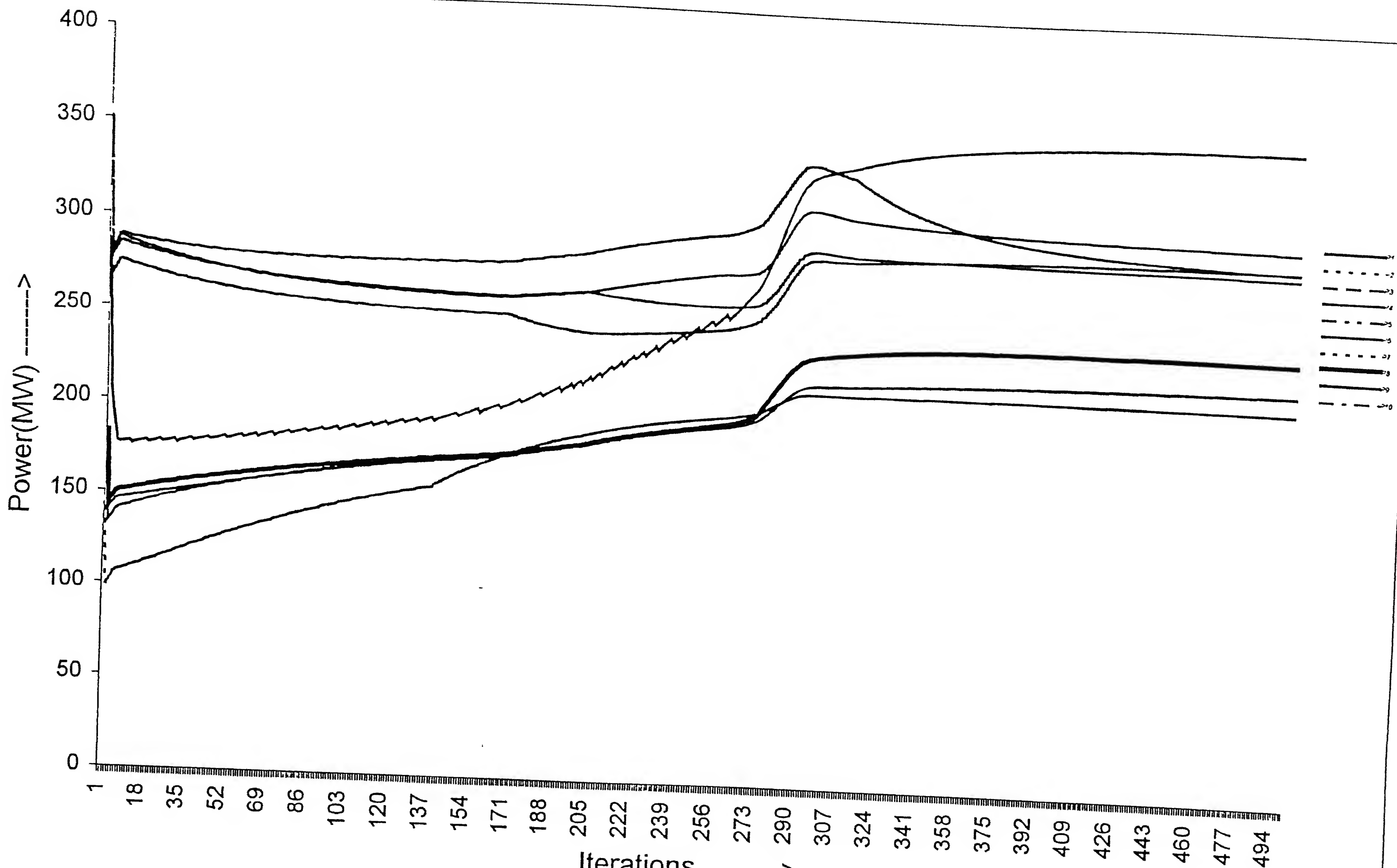


Fig.4.8.VARIATION OF POWERS FOR PROBLEM 4.4.2(CASE 4) DUE TO HOPFIELD UPDATION

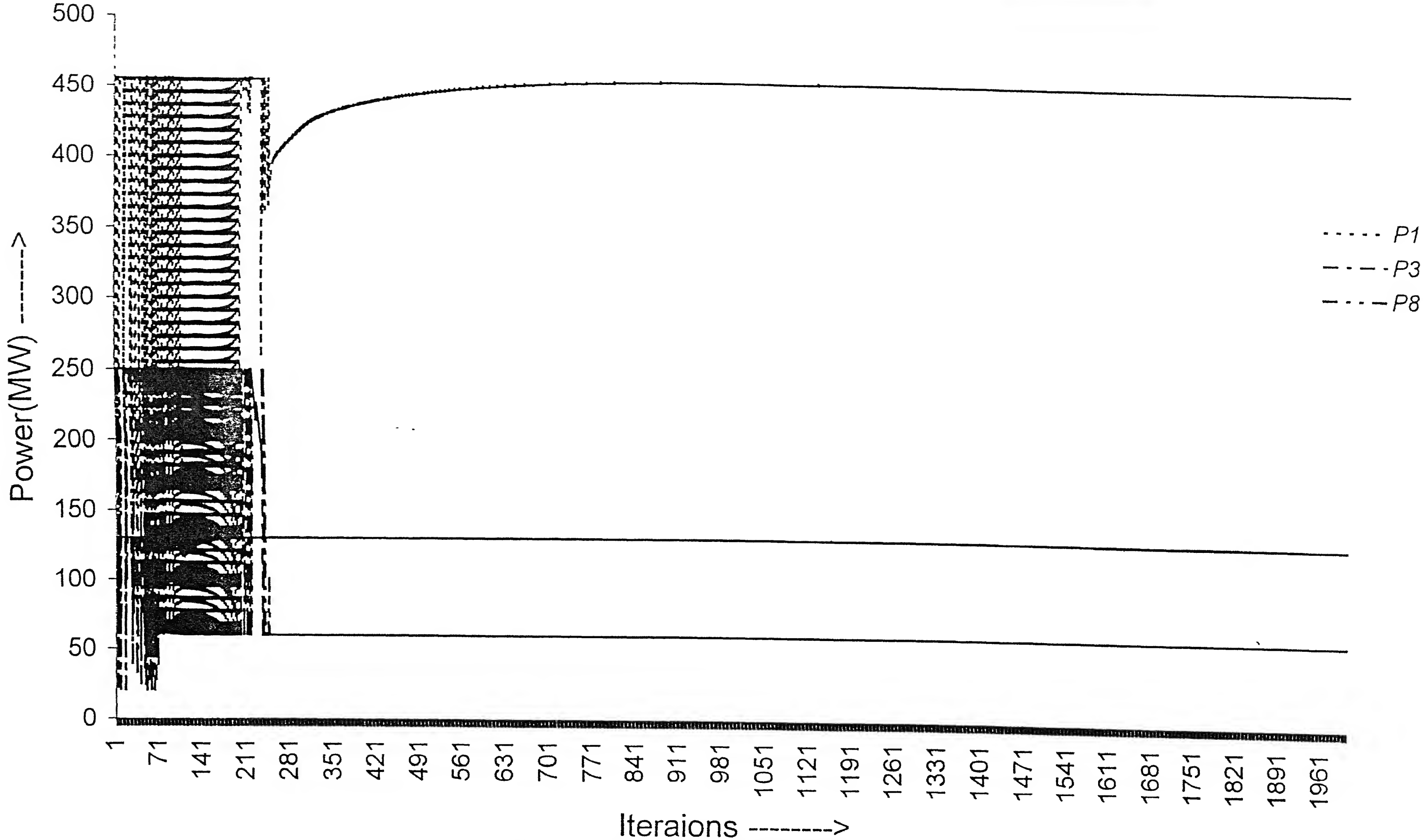


Fig4.9.VARIATION OF POWERS FOR PROBLEM 4.4.4.DUE TO HOPFIELD UPDATION

Chapter 5

Conclusions and Recommendation for Future Work

5.1. Comparison of various results

Before deriving the final conclusions, the results obtained from different methods, to the various problems, discussed in section 3.4.and in section 4.4.have been compared. These results have also been compared with that of the results obtained from the conventional methods, taken from the respective literature, mentioned at each problem.

The comparison of results has been presented in tables 5.1. through 5.4.

In table 5.1., the results obtained from problems 3.4.1. and 4.4.1.have been compared with the one obtained from the standard Lagrange method. In table 5.2., the results obtained from problem 3.4.2. and 4.4.2. have been compared with the one obtained from hierarchical structure method [5].In table 5.3., the results obtained from problem 3.4.3.and 4.4.3.have been compared with that of the results obtained from [9]. In table 5.4., the results obtained from problem 3.4.4.(case 1) and 4.4.4.have been compared with that of the results obtained from[7].

Table 5.1. Comparison of results for the problem 3.4.1.

	P_1	P_2	P_3	Total power[MW]	Total cost [$/h]
LaGrange's method					
Case 1	393.2	334.6	122.2	850	8194.3
Case 2	600.0	187.1	62.9	850	7252.1
Case 3	435.1	300	130.7	865.8 (loss=15.8)	8344.3
Simulated annealing method					
Case 1	393.504	334.405	122.192	850	8194.356
Case 2	599.997	184.246	65.756	850	7252.88
Case 3	434.639	294.434	136.636	865.709 (loss=15.709)	8344.892
Simulated annealing applied to Hopfield network					
Case 1	395.8828	329.249	124.417	849.5488	8191.73
Case 2	598.8209	185.884	64.266	848.9709	7244.679
Case 3	429.6422	293.488	141.836	864.966 (loss = 15.6)	8338.498

Table 5.2. Comparison of results for the problem 3.4.2.

Hierarchical structure method									
S	U	2400MW		2500 MW		2600 MW		2700 MW	
		F	Gen.	F	Gen.	F	Gen.	F	Gen.
1	1	1	193.2	2	206.6	2	216.4	2	218.4
	2	1	204.1	1	206.5	1	210.9	1	211.8
	3	1	259.1	1	265.9	1	278.5	1	281
	4	3	234.3	3	236	3	239.1	3	239.7
2	5	1	249	1	258.2	1	275.4	1	279
	6	1	195.5	3	236	3	239.1	3	239.7
	7	1	260.1	1	269	1	285.6	1	289
3	8	3	234.3	3	236	3	239.1	3	239.7
	9	1	325.3	1	331.6	1	343.3	3	429.2
	10	1	246.3	1	255.2	1	271.9	1	275.2
Total load		2401.2		2501.1		2599.3		2702.2	
Total cost		488.5		526.7		574.03		625.18	

Simulated annealing method									
S	U	2400MW		2500 MW		2600 MW		2700 MW	
		F	Gen.	F	Gen.	F	Gen.	F	Gen.
1	1	1	189.541	2	206.5399	2	216.099	2	226.572
	2	1	202.421	1	206.522	1	211.147	1	215.486
	3	1	254.087	1	265.8019	1	277.99	1	291.611
	4	3	232.793	3	235.96089	3	239.0749	3	242.3739
2	5	1	242.214	1	258.0937	1	275.895	1	292.847
	6	3	233.014	3	235.926	3	239.157	3	242.227
	7	1	252.856	1	268.934	1	287.061	1	302.514
3	8	3	232.979	3	235.7704	3	239.178	3	242.296
	9	1	320.188	1	331.32388	1	342.461	1	355.1022
	10	1	239.907	1	255.127	1	271.935	1	288.9867
Total load		2400		2500		2600		2700	
Total cost		481.724		526.2389		574.3857		626.2545	

Simulated annealing applied to Hopfield Network									
S	U	2400MW		2500 MW		2600 MW		2700 MW	
		F	Gen.	F	Gen.	F	Gen.	F	Gen.
1	1	1	189.4798	2	206.1095	2	215.875	2	224.905
	2	1	202.22	1	206.3079	1	210.7318	1	215.1414
	3	1	253.8197	1	265.8326	1	278.821	1	292.304
	4	3	232.9938	3	235.896	3	239.0287	3	242.1523
2	5	1	241.4418	1	257.6237	1	275.0909	1	292.629
	6	3	232.994	3	235.8964	3	239.0298	3	242.156
	7	1	253.1695	1	268.8056	1	285.7755	1	303.005
3	8	3	232.9938	3	235.895	3	239.0287	3	242.152
	9	1	320.3858	1	331.478	1	343.4448	1	355.25
	10	1	239.43	1	254.9978	1	271.925	1	288.964
Total load		2398.93		2498.84		2598.75		2698.66	
Total cost		481.264		525.704		573.758		625.541	

Table 5.3. Comparison of results for problem 3.4.3.

Method mentioned in,[9]						
Strategy	**SO_2 limit (tons)**	**NO_x limit (tons)**	**Fuel (MBTU)**	**Cost ($)**	**SO_2 (tons)**	**NO_X (tons)**
Min Cost			122356	196422.9	72.904	19.104
Min SO2			122623	203903.6	71.493	17.541
Min Nox			123651	204.290.7	72.134	16.027
Min Fuel			121836	198766.1	72.513	18.523
Min Cost with SO2 Limits	72.198		121894	199729.8	72.202	18.143
Min Cost with NOx Limits		17.566	122269	198806.8	72.613	17.563
Min cost + emission allow with SO2 limits	72.198		121894	221388.2	72.203	18.144
Min cost with SO2 and NOx limits	72.198	17.566	122011	199425.6	72.195	17.563
Simulated annealing method						
Strategy	**SO_2 limit (tons)**	**NO_x limit (tons)**	**Fuel (MBTU)**	**Cost ($)**	**SO_2 (tons)**	**NO_X (tons)**
Min Cost			122357	196493	72.557	18.853
Min SO2			122708	204263	70.699	17.727
Min Nox			123642	204296	71.925	15.978
Min Fuel			121841	198766	71.803	18.437
Min Cost with SO2 Limits	71.628		122333	199176	71.491	18.21
Min Cost with NOx Limits		17.4155	122752	199009	72.22	17.328
Min cost + emission allow with SO2 limits	71.628		122678	202411	71.626	16.62
Min cost with SO2 and NOx limits	71.628	17.4155	122799	201868	71.623	17.083
Simulated annealing applied to Hopfield						
Strategy	**SO_2 limit (tons)**	**NO_x limit (tons)**	**Fuel (MBTU)**	**Cost ($)**	**SO_2 (tons)**	**NO_X (tons)**
Min Cost			121863	200709	71.442	16.62
Min SO2			121906	200954	71.432	16.67
Min Nox			122244	201562	71.627	16.615
Min Fuel			121167	201314	71.603	16.66
Min Cost with SO2 Limits	71.437		121957	200814	71.432	16.67
Min Cost with NOx Limits		16.618	121955	200807	71.432	16.62
Min cost + emission allow with SO2 limits	71.437		122124	201164	71.432	16.635
Min cost with SO2 and NOx limits	71.437	16.618	122544	201653	71.432	16.62

Table 5.4. Comparison of results for problem 3.4.4.(case1)

	Windowing method,[8]	Simulated annealing method	Simulated annealing applied to Hopfield Network
Unit	**Power (MW)**	**Power (MW)**	**Power (MW)**
1	455	453.754	450.434
2	455	419.615	450.4308
3	130	129.922	130
4	130	129.929	130
5	317.835	433.0738	335
6	460	364.9105	455.433
7	465	463.168	460.4346
8	60	60.0416	60
9	25	25.001	25
10	20	20.297	20
11	20	20.0637	20
12	57.166	75.203	57.208
13	25	25.02	25
14	15	15	15
15	15	15	15
Total load	2650.01	2650	2648.94
Total coat	32542.45	32620	32585.1

5.2. General Conclusions

A general Simulated Annealing based Economic Load Dispatch algorithm has been presented. Methods for incorporating the transmission losses, emission dispatch constraints and prohibited zone constraints of the Economic Load Dispatch problem, into the Simulated Annealing algorithm have been worked out. Also methods for incorporating different types of cost functions like quadratic, piecewise quadratic and polynomial cost functions into the algorithm have been worked out. The effect of cooling schedule on the performance of the Simulated Annealing algorithm has been worked out in detail. The ability of the algorithm to find the global or near global optimum solution has been demonstrated by several test examples. An attempt has been made to apply Simulated Annealing Algorithm to update the weights of Hopfield Network, so as to drive the Hopfield Network to produce global optimum solution.

The dispatch results obtained by applying Simulated Annealing Algorithm to various problems discussed are proven to be either more economical or equally economical in all the cases compared to the conventional methods, apart from having several advantages which are summarized below.

- The solution procedure is completely independent of the type of fuel cost characteristic of the generators.
- Its solution procedure and also the convergence property will not get effected by the inclusion of parametric and functional inequality constraints.
- Exact dispatch solution to meet the load demand and the transmission losses is guaranteed.
- There is no need to evaluate LaGrange multipliers and penalty factors, which not only saves computer memory but also makes the computational procedure very simple.
- The computer memory requirement is very low.

The advantages of applying Simulated Annealing algorithm to Hopfield Network are,

- Application of this algorithm to update the weights of Hopfield Network, makes the convergence of Hopfield Network independent of the selection of weighting factors of cost function, A and B.
- As this method eliminates the requirement of finding the weight matrix from the ELD problem, one can design their own network to apply Hopfield technique and can try to improve the fault tolerance of the network.

When Simulated Annealing is applied to update the weights of Hopfield Network, there are no constraints imposed on the weights which made the weights to stay at undesired locations in some situations, leading to the malfunction of the Hopfield Network. So some more work is needed in this area.

As the algorithm itself is a random search process, the main disadvantage of the discussed Simulated Annealing algorithm is that the computational time is high.

5.3. Scope for Future Work

- Considerable work has to be done to improve the speed of the algorithm.
- To apply the Simulated Annealing Algorithm to Hopfield Network, work has to be done in the area of selection of weights and updation of the weights.
- One can try to apply the proposed method, by taking different Networks, than those are obtained from the ELD problem, and can try to derive different Networks for which Hopfield method can be applied. And then one can study the fault tolerance of those networks, and can try to come up with a good hardware implementation.

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